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DEVELOPMENT OF AI PROCEDURES FOR DEALING WITH THE EFFECTS OF EPISODAL EVENTS ON CROP TEMPORAL SPECTRAL RESPONCE

AND

DEVELOPMENT OF AI GUIDELINES FOR CORN AND SOYBEAN LABELING

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Annual Progress Report:

DEVELOPMENT OF AI PROCEDURES FOR DEALING WITH THE EFFECTS OF EPISODAL EVENTS ON CROP TEMPORAL-SPECTRAL RESPONSE

AND

DEVELOPMENT OF AI GUIDELINES FOR CORN AND SOYBEAN LABELING

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This report describes activity carried out in support of crop type labeling and area estimation in the Supporting Research Project.

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16. Abstract

This report documents the result of work conducted in support of manual analysis for crop type identification with Landsat and ancillary data.

Temporal and spectral variability of small grains for several years was evaluated in order to advise AI's of the Effects of Episodal Events upon Crop temporal-spectral response. A procedure for fitting a curve through Landsat spectral data for specific crop fields was developed. The fitted curve represents the spectral response of the field over time. The curve can be considered then as a spectral crop calendar.

Temporal and spectral characteristics of corn, soybeans, sunflowers, sugar beets, and sorghum were evaluated and interpretation guidelines for use by multicrop analysts were developed.

An integrated analyst-machine interpretation procedure was also developed.

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SUMMARY

TASK I: DEVELOPMENT OF AI PROCEDURES FOR DEALING WITH THE EFFECTS OF EPISODAL EVENTS ON CROP TEMPORAL-SEPCTRAL RESPONSE

The primary objective of this task was to measure and quantitatively describe for the analyst the year-to-year variation in crop temporal-spectral response patterns due to any year-to-year variation in the physical environment.

A standard method for representing crop temporal-spectral response that was consistent among segments and years was developed in order to reliably measure and quantitatively describe year-to-year variation for the analyst. The method used discrete Landsat acquisitions to estimate a continuous function which represented a crop's spectral response pattern over its growing season. This method generated a consistent framework within which comparisons of temporal-spectral response characteristics among years, segments, and crops could be carried out. (See Section 1.3.4.).

Within any particular segment, the year-to-year variation in temporal-spectral response characteristics was in general highly significant relative to field-to-field variation. This observation underscored the need for the AI to calibrate labeling guidelines to the segment and year being analyzed. Table 1.7 summarizes both the observed year-to-year within-segment variation and the among segment-year variation in a useful way for the AI. (See Sections 1.4.1 and 1.4.1.1.)

The nature and magnitude of field-to-field temporal-spectral variability, within each segment-year combination, was examined and statistically tested for year-to-year consistency. In one third of the cases, the field-to-field variation was found to be not constant from year to year. A summary of the observed field-to-field variation is presented in Table 1.9. (See Section 1.4.1.2.)

Using Spring Wheat data only, all pairs of temporal and spectral variables were examined for significant correlation. There was no significant correlation between the spectral variable F_{max} (maximum GRABS amplitude) and any of the temporal variables. However, there were observed highly significant correlations among some of the temporal variables. (See Section 1.4.1.3 and Table 1.10.)

Multiple linear regression analyses were performed on Spring Wheat data, using temporal and spectral variables as dependent variables, and precipitation and temperature variables as independent variables. The multiple regression models themselves offered little insight into the causal mechanism linking meteorological factors to spectral response pattern variation. However, two general types of relationships appeared consistently throughout the results. These were 1) a positive correlation between precipitation and temporal variables; and 2) a negative correlation between temperature and spectral-temporal variables. (See Section 1.4.2 and Table 1.14.)

TASK II: SUMMARY

Subtask A:

To establish baseline accuracy levels for first-generation summer crop labeling guidelines and determine remaining problem areas in labeling, an interpretation test was administered to seven UCB analysts. The test data set was composed of five central Corn Belt and five peripheral Corn Belt segments. Average labeling accuracies across all segments and analysts were 90.64 per cent for corn, 85.68 for soybeans, and 87.14 for combined summer crops, including sunflowers, sugar beets and sorghum. Analysis of variance indicated significant segment effect on variation but no significant analyst effect on variation. Qualitative evaluation of incorrect labels disclosed that a large number of summer crop errors (almost 50 per cent within the five central Corn Belt segments) were due to analyst inexperience in the use of spectral aid data products and thus the analysts didn't optimally apply the guidelines. The remaining errors, were due to inadequate guidelines, lack of data separation, or poor quality data. The following problem areas were identified for further corn/soybean labeling guideline research: (1) separation of "non-green" soybeans (low relative GRABS values) from corn, (2) separation of "non-green" sunflowers from corn, (3) separation of corn from sorghum, and (4) separation of summer crops from alfalfa, pasture, and range. Examination of temporal-spectral data distribution from test segments yielded guideline modifications related to problem 2 and possible solution of problem 1 which require further study. Other problem areas not specifically in the domain of guideline research were identified, in particular the need for improved analysis procedures that would enable the AI to assimilate a large amount of data efficiently and accurately.

Subtask B:

The Delta Function Stratification (DFS) Procedure which was developed to stratify a segment into Small Grains Probability Strata was extended to the corn/soybean situation and espanded to enable crop Group/land use stratification in a milticrop situation. In this procedure a green vegetation indicator for which a green vegetation detection threshold has been established, is used to determine the temporal pattern classes present within a scene. The temporal pattern classes are then assigned to crop group/land use strata based on evaluation using adjusted crop calender data. The expanded procedure was applied to both cluster data and pixel-by-pixel data. The procedure was tested for eleven segments and the classification results for the pixel-by-pixel procedure compared favorably with the cluster procedure. In addition, the pixel-by-pixel procedure offered some advantages over the cluster procedure in terms of ease of processing amd number of acquisitions that could be processed.

Subtask C:

An effective and efficient crop type labeling procedure was developed and partially exercised within the interpretation tests discussed in Subtask A. Analysis within this procedure proceeds from general level analysis for crop group to the specific level of analysis for crop type determination of a specific labeling target. The general level analysis utilized the DFS procedure described in Subtask B and proceeds to finer levels of stratification using additional linear discriminant until the final level of crop type analysis at the specific labeling target.

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TASK I: DEVELOPMENT OF AI PROCEDURES FOR EPISODAL EVENTS

By

C. M. Hay, C. A. Kuretz, E. J. Sheffner, and B. L. Wood

1.0 TASK I: DEVELOPMENT OF AI PROCEDURES FOR DEALING WITH THE EFFECTS OF EPISODAL EVENTS ON CROP TEMPORAL-SPECTRAL RESPONSE.

1.1 INTRODUCTION AND OBJECTIVE

Variation in the temporal-spectral characteristics of a crop type can pose a problem for an analyst if he is not aware of the possible magnitude and nature of the variation. Within specific segments, few cropped fields of any crop type ever appear exactly the same as site-and year-specific training examples or previously interpreted fields. Acquisition timing, scene background spectral characteristics, and spatial context all vary from site to site. Thus each new segment is a unique interpretation situation. Events such as drought, excessive moisture, severe cold, and winterkill can and will cause extreme shifts from the expected crop temporal-spectral response patterns. In order to successfully accomplish each new interpretation an analyst must be able to adjust his crop-specific a priori expectations for each new segment and/or year to be interpreted. Within LACIE, it was observed that in "abnormal", extreme situations, analysts experienced difficulty in adjusting their a priori expectations for specific crops (i.e. small grains). They were unable to successfully relate the observed crop temporal-spectral response patterns within a drought affected area to their training experience, normal crop calendar data, and/or other ancillary data. This led to lower interpretation accuracies within these affected areas.

Therefore, in order to aid the analyst in his interpretation, a need existed to describe the variation in temporal-spectral response due to variation in the growth environment of the crop. This was initiated in FY 78's effort on this task. However, results from the FY 78 effort showed that there was significant year-to-year variation, in both the temporal pattern of crop development and in the spectral response of the small grain crop, between years that were not considered extreme in their physical environmental conditions. Thus the term "episodal event" as applied in this FY 79 task was defined to be any significant variation in crop temporal-spectral response regardless of cause.

The primary objective of this task therefore was to measure and quantitatively describe for the analyst the year-to-year variation in crop temporal-spectral response patterns due to any year-to-year variation in the physical environment.

Since the desire was to measure, compare, and describe the crop temporal-spectral variation, a method for representing crop temporal-spectral response patterns that was consistent among segments and years was needed. Thus, a secondary objective of this task was to develop such a consistent representation method, so that extracted crop temporal-spectral parameters would be comparable among segments and years.

Thirdly, in an attempt to understand the causal relationships between spectral variation and physical environment variation, an additional objective was to relate year-to-year temporal-spectral variation to observed meteorological variation.

1.2 GENERAL APPROACH

Crop temporal-spectral response patterns for several years of Landsat and ancillary data (including identified "abnormal" years) were examined. The data set was assembled from Landsat MSS data for twelve LACIE U.S. Great Plains segments, acquired from 1975 through 1978 spring and winter wheat growing seasons. This data base was chosen because of the good multi-year set of acquisitions that existed for the wheat crop. The MSS data was sun angle and haze corrected, and a green vegetation indicator was calculated for each pixel. Wheat fields in specific segment-year combinations were then sampled.

A standard method for representing crop temporal-spectral response that was consistent among segments and years was developed in order to reliably determine and quantitatively describe year-to-year variation for the analyst. The method that was developed used discrete Landsat acquisitions to estimate a continuous function which represented a crop's spectral development pattern over its growing season. Using this procedure, the average temporal-spectral response of a crop for a specific segment-year combination was determined. Furthermore, the procedure allowed estimation of both field-to-field (within segment-year) and year-to-year (within segment) variability.

In order to gain some understanding of possible causal factors for the observed year-to-year temporal-spectral variation, variation in year-to-year climatological variables was studied. A meteorological data set was extracted from NOAA-NCC climatological Data reports. This data set consisted of temperature and precipitation variables measured at one selected weather station close to each of the study segments. Multiple linear regression models were used to detect relationships between these weather variables and the temporal-spectral variables determined from the Landsat data.

1.3 DETAILED APPROACH

1.3.1 DETERMINATION OF STUDY SEGMENTS

As part of the FY 78 effort on this task, areas within the U.S. Great Plains that had experienced significant drought stress in the crop years 1975-77 (the extent of the LACIE data set) were identified from USDA-SRS Crop-Weather Bulletons and LACIE reports. Areas free of significant drought in these years were also identified for control purposes. Twelve LACIE blind sites were selected from these areas

based on 1) number of years of Landsat and ground data available, 2) adequate within-year acquisition histories, 3) diversity in number of drought stress years, and 4) geographical diversity. Figure 1.1 shows the locations of the selected segments. Transition year 1978 data was added to the data set where available.

1.3.2 WITHIN-SEGMENT SAMPLING

PFC image products were manually screened for cloud cover, and the best three to six acquisitions were chosen for each segment-year. Wheat fields from each segment-year were selected according to a systematic sampling scheme: if a sampling point fell within or next to a wheat field of adequate size, the field was accepted. Only spectral data from interior pixels was used, and a two pixel border around the interior was preferred. Sampling continued until fifteen fields were selected or until the sampling scheme was exhausted.

Ground data was available for all of the 1978 and 1977 segments, but only for segments 1166, 1637 and 1851 in 1976. Wheat field identification for the remainder of the 1976 segments and for all 1975 segments was accomplished by manual interpretation. The 1977 sample was augmented by those of the 15 special wheat fields that were of adequate size and not already selected by the sampling strategy.*

1.3.3 PREPROCESSING OF THE DATA

The digital spectral data for the selected acquisitions was sun angle and haze corrected using the XSTAR Procedure developed by ERIM. Corrected data was used for all spectral analyses in this task. The Kauth-Thomas Tassel Cap (TC) Transformation was applied, and a new variable GRABS was generated by the equation

$$GRABS = GREENNESS\ (TC\text{-}2) - .09178 \times BRIGHTNESS\ (TC\text{-}1) + 5.58959.$$

The transformation yielding GRABS was obtained by projecting the equation 2 x MSS7/MSS5 = 1.1 onto the Greenness-Brightness Plane of Tassel Cap space using constant values for Yellow Stuff ((TC-3) = 11.208) and Non-Such ((TC-4) = 1.36). The invention of GRABS was an attempt to develop a green vegetation indicator for which a consistent (independent of site and acquisition) threshhold value for green vegetation detection could be specified, and which therefore would not require segment-year-specific calibration. For further discussion of GRABS, see Section 2.4.2.

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* *15 fields per segment, with ground observations at 18-day intervals, were provided for LACIE Phase III blind sites by JSC.*

1.3.4 DEVELOPMENT OF A CONSISTENT MEASUREMENT FRAMEWORK

In that Landsat samples the spectral data for a given location at best only once every 18 days (one satellite) or 9 days (two satellites), the directly observed spectral values are a function of the time of acquisition. In order to determine the yearly variation in crop temporal-spectral response, therefore, it is first necessary to develop a measurement framework from which acquisition independent temporal-spectral variables can be determined. One helpful way to represent crop temporal-spectral response which is acquisition independent, is to estimate a continuous spectral response pattern or curve for a crop as a function of time. A method was developed for determining such a continuous curve which represents the growing season specific temporal plot of spectral response (spectral crop calendar) for a field. From such a curve, one can determine major spectral events (spectral biostages) for a crop (e.g. maximum amplitude of a vegetation indicator, date of first green canopy detection, date of maximum amplitude of a vegetation indicator) and assess the year-to-year variation in such events.

The function used to generate the continuous temporal plot was

$F = T^{B_1} e^{B_2 T^2 + B_3}$, where F = the value of the green vegetation indicator, T = Julian date, and B_1, B_2, B_3 are coefficients estimated by a least squares procedure. This function was first used by the Environmental Research Institute of Michigan (ERIM) to generate a temporal plot of Greenness* (TC-2) values for spring wheat fields in North Dakota. This particular function was chosen for its appropriate shape and its adaptability by logarithmic transformation to estimation by least squares linear regression.

In the FY 78 effort, a single curve was generated for each segment-year combination of data. Spectral data reduced to field means were used as input to a SPSS least squares linear regression program. This program fit the non-linear function to the spectral data by means of a logarithmic transformation. Two significant limitations were inherent in this approach: 1.) there was no obvious variance term to associate with a temporal-spectral value (e.g. date of maximum amplitude) derived from such a segment-average curve; and 2.) the curve-fit was extremely poor in some cases, especially when the within-segment (i.e. field-to-field) variation was large.

In an attempt to overcome these limitations, the approach was modified during the FY 79 effort. Using individual pixels as input data to the same SPSS least squares linear regression program, a separate curve was fit to each field. The segment-average values of the temporal-spectral variables were obtained by averaging the corresponding values from individual fields. Thus, each segment-average

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* Greenness is a green vegetation indicator generated from ERIM's Tassel Cap Transformation of Landsat 4-channel MSS data. See Kauth-Thomas, 1976 for details.

value had an associated variance based on field-to-field variation. Furthermore, the curve-fitting was more precise since within-field (pixel-to-pixel) variation was of a much lower order than within-segment (field-to-field) variation.

In spite of this modification, one problem still remained. The function when fit by the SPSS linear regression program tended to consistently underestimate the value of the maximum amplitude. This underestimation of the peak was obvious from visual comparison of the plotted pixel data with a plot of the generated curves. To solve this problem, a nonlinear least squares program* was used to estimate the coefficients of the function instead of the previous logarithmic transformation and linear regression method. The use of the nonlinear program dramatically improved the overall fit of the curve (as measured by R^2 values), and improved the accuracy with which the peak vegetation indicator value was determined. Table 1.1 compares R^2 values for the linear and nonlinear methods for one test segment.

1.3.5 TEMPORAL-SPECTRAL VARIABLES EXAMINED

The equations generated by the nonlinear curve-fitting program were used to calculate the following variables for each wheat field:

- F_{max} = maximum GRABS value
- T_{max} = Julian date of maximum GRABS
- T_b = Julian date on which GRABS = 2 before peak
- T_a = Julian date on which GRABS = 2 after peak
- $T_{max} - T_b$ = number of days between first detectability and peak
- $T_a - T_b$ = number of days between first detectability and harvest.

The corresponding average values for each segment-year were calculated by taking the unweighted arithmetic mean over all sampled fields within that segment-year. These values are presented in Table 1.2. The unweighted mean was chosen after comparisons between the unweighted mean and the weighted means based on R^2, number of pixels, residual mean square or combinations of these had been made for segment-year combinations that showed the most variation. In all cases, the differences among these

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* The nonlinear least squares program used is called VARPRO, and was developed by Golub, Pereyra and Bolsted at Stanford University.

estimates were trivial for the present context. However, it may be useful in a future context (for example, the use of fitted curves to detect crop biostages) to reconsider the use of weighted means to estimate segment average spectral values. Two winter wheat segments, 1032 and 1166, lacked adequate acquisition histories for valid temporal-spectral response pattern representation by curve-fitting. For this reason, they do not appear in Table 1.2.

1.3.6 CLIMATOLOGICAL AND PHYSICAL ENVIRONMENTAL VARIABLES EXAMINED

In order to increase the value to the analyst of the temporal-spectral variation information, an attempt was made to discover relationships between the yearly temporal-spectral variation and the yearly meteorological and crop growth environment variations for spring wheat. Several environmental variables were calculated for each spring wheat segment-year combination using data extracted from NOAA Climatological Data Reports.

The environmental variables were:

a.) P1 = accumulated departure from normal (30 year mean) precipitation from September 1 to December 31 of previous year.

b.) P2 = accumulated departure from normal precipitation from January 1 to T_b

c.) P3 = accumulated departure from normal precipitation from T_b *to* T_{max}

d.) PR(PJ) = accumulated precipitation between planting and jointing stages

e.) PR(HM) = accumulated precipitation between heading and milk stages

f.) TX(JF) = mean daily maximum temperature between jointing and flag-leaf

g.) TX(FH) = mean daily maximum temperature between flag-leaf and heading

h.) TX(HM) = mean daily maximum temperature between heading and milk

i.) TX(MD) = mean daily maximum temperature between milk and and dough stages.

P1 represents moisture accumulated from the end of harvest in the preceeding crop year to after germination of the next season's winter wheat crop.

P1 + P2 represents moisture accumulated from the end of harvest in the preceeding crop year to a.) after germination of the next season's spring wheat crop or b.) spring "green up" of the next season's winter wheat crop.

P3 represents the moisture falling during the wheat crop growing season from first detection of green vegetation to date of maximum GRABS response.

Variables d - i and some functions of these were identified by Feyerherm (Feyerherm, 1979) as having a significant effect on crop yeild and were therefore included on the assumption that meteorological events affecting crop yield may also affect crop temporal-spectral response. In order to compute variables d - i from the daily temperature and precipitation records, it was first necessary to estimate spring wheat planting date for each segment-year. The planting date model used was that given by Feyerherm (Feyerherm, 1979). This model accumulates Warming/Planting days until a threshold value is attained. Using this threshold date as the estimated planting date, the Robertson Biometeorological Time Scale (BMTS) (Robertson, 1968) was used to generate dates for each successive biostage from emergence through ripe. These dates defined the time intervals for computing the above precipitation and temperature variables. The values of these variables are presented in Table 1.3.

An analogous effort was planned for winter wheat, but application of the curve-fitting program to winter wheat segments revealed a critical lack of important acquisitions in several segment-years. There were not enough good segment-years for a valid exploration of the regression models as planned.

1.4 RESULTS AND CONCLUSIONS

1.4.1 YEAR-TO-YEAR TEMPORAL-SPECTRAL VARIATION

The temporal-spectral variables described in Section 1.3.5 and presented in Table 1.2 were tested for significant year-to-year variation within each segment using one-way Analysis of Variance. Table 1.5 presents the levels at which F-ratios for year-to-year effect were significant in these analyses, "ns" indicating non-significance at the .05 level. Significance was indicated in seventy-five percent (forty-five of sixty) of the F-tests performed.

Comparison of these results with the results of analogous analyses reported for FY 78, based on Green Number rather than GRABS, revealed some disagreement between the two years' findings of significance. In

particular, in FY 78, F_{max} for segments 1602, 1652 and 1175 and T_{max} for 1175 were found non-significant, and T_{max} for 1652 was significant at the .001 level. The change from Green Number to GRABS could partially account for this disagreement. Although both variables are based on Tassel Cap Greenness, Green Number is acquisition dependent and could yield a profile which differs from the GRABS profile. But it was felt that the disagreement could also be attributed to two improvements in the curve-fitting procedure, which made the current year's results more reliable. First, curve-fitting in FY 78 was done on a whole-segment basis after reducing individual pixel data to field means. Thus field-to-field variation was not used for assessing true within-segment variability in the temporal and spectral variables. The present approach of retaining individual pixel data and fitting a curve to each field separately allows year-to-year variation in the segment-average temporal and spectral values to be tested for significance against field-to-field within-segment variation. Second, the present curve-fitting program is based on nonlinear least squares rather than logarithmic transformation and linear regression as was used in FY 78. Curves estimated by the nonlinear method fit the data better and hence provide more accurate estimates of the temporal and spectral variables of interest. The development of the curve-fitting procedure was discussed in detail in Section 1.3.4.

The bottom of Table 1.5 indicates anomalous years for each segment. An anomalous year was defined to be a year in which the segment's county per acre wheat yield differed by at least one standard deviation from the county's mean yield. Means and standard deviations were based on periods varying from five to twelve years for the counties involved. It was anticipated that segments experiencing anomalous yield would exhibit significant variation in some of the temporal-spectral variables. This was found to be true. With the exception of the temporal variables for segment 1652, all temporal and spectral variables showed significant year-to-year variation in those segments for which anomalous years were identified.

However, it must be noted that there was significant year-to-year temporal and/or spectral variation in those segments for which no amonalous year was identified. Thus, the year-to-year variation in wheat's temporal-spectral response pattern can be significant, and thus affect the AI's ability to label accurately, even among years of relatively average yield.

This last point is crucial to understanding the motivation of this task. In order to accurately label crops, the AI needs 1) an adequate awareness of possible year-to-year temporal-spectral variation, regardless of its causes or consequences, and 2) a better understanding of the causal relationships between environmental variables and temporal-spectral response. The latter will enable the AI to more effectively calibrate ancillary data and a priori information to the specific segment and year being analyzed.

1.4.1.1 QUANTITATIVE DESCRIPTION OF YEAR-TO-YEAR TEMPORAL-SPECTRAL VARIATION

As a summary of the year-to-year temporal and spectral variation observed for the study segments, the variables listed in Table 1.2 were reduced to year-to-year ranges and presented in Table 1.6. Within each of two separate groups for spring and winter wheat, ranges were computed for each segment individually, averaged over segments (Mean Range), and computed over all segment-year combinations in the group (Total Range). Thus, the Mean Range of any particular variable represents the average year-to-year within-segment range of that variable. By comparison, the Total Range represents the observed range of all the yearly segment means among all segments in the crop group (spring or winter wheat).

The Total Range is always at least as large as the largest individual segment entry above it. This fact is inherent in the computations involved. However, the fact that the Total Range consistently greatly exceeds the largest of the individual segment entries indicates considerable segment-to-segment variation. The observation that Total Range is generally at least twice Mean Range is further evidence of the magnitude of segment-to-segment variation. For the AI attempting to identify crops in a particular segment and year based on guidelines and expectations derived from his experience of other segment-year combinations, the information contained in both Mean Range and Total Range is valuable. Therefore, the information in Table 1.6 is presented again in Table 1.7 in a form more useful and accessible to the AI.

1.4.1.2 YEAR-TO-YEAR VARIATION IN FIELD-TO-FIELD WITHIN-SEGMENT CROP TEMPORAL-SPECTRAL HOMOGENEITY

In order to accurately label the crops in a specific segment-year conbination, the AI needs to understand the nature and magnitude of field-to-field variation within crop type and within segment-year, i.e., field-to-field temporal-spectral homogeneity. Within any specific segment-year combination, the field-to-field homogeneity of a particular temporal or spectral variable is measured by the standard deviation associated with that variable. Table 1.2 presents the sample (from sampled wheat fields) standard deviations for all temporal and spectral variables in all segment-year combinations. These sample standard deviations were used in a statistical test of the significance of the observed year-to-year variation in field-to-field homogeneity.

The statistical test used was Bartlett's test of the equality of a number of population variances. For each segment and for each temporal and spectral variable, Bartlett's test tested the hypothesis that the within-segment variance (square of the standard deviation) was constant from year to year. Table 1.8 presents the results of the application of Bartlett's test. A significant result indicates that the variance was not constant from year to year; that is, that year-to-year variation in field-to-field homogeneity was significant for that variable in that segment.

One third of the tests (nineteen of sixty) indicated significance, and the significant results were distributed among all segments (except 1851) and all temporal and spectral variables. This result raises an important technical statistical point. The theory of the Analysis of Variance is based on the underlying assumption that the error variance is constant over the entire experiment. In the present context, this assumption means that the within-segment variance (and the phenomenon it measures, field-to-field temporal-spectral homogeneity) must be constant from year to year in order that the Analyses of Variance described in Section 1.4.1 and presented in Table 1.5 be valid. But in one third of the cases tested, Bartlett's test indicated that the assumption of constant variance was not supported by the data. Therefore, it must be remembered that the objectives of this task are the measurement and quantitative description for the AI of temporal-spectral variation. The accomplishment of this objective does not require the rigorous statistical testing of preconceived hypotheses. Although the results of statistical tests have offered valuable insights into the nature and magnitude of temporal-spectral variation, it is measurement and description that are of greatest value to the AI for increased labeling accuracy.

Furthermore, the field-to-field within-segment variance of some spectral or temporal feature could be a valuable indicator of some crop or environmental condition of which the AI needs to be aware. Thus, significant year-to-year variation, as detected by Bartlett's test, could contribute information for the labeling problem.

A summary of observed field-to-field within-segment-year crop temporal-spectral homogeneity is contained in Table 1.9. For each temporal and spectral variable, and for spring and winter wheat separately, the minimum and maximum sample standard deviations observed among all segment-year combinations were selected from Table 1.2 and are presented in Table 1.9. Also presented is the pooled within-segment-year root mean square deviation for each variable and each crop type. This table gives the AI an idea of the minimum, maximum, and average within-segment-year standard deviations that were observed for spring and winter wheat, and hence, a quantitative idea of the magnitude of field-to-field variability.

1.4.1.3 CORRELATIONS AMONG TEMPORAL AND SPECTRAL VARIABLES

Table 1.10 presents simple linear correlation coefficients for all pairs of temporal and spectral variables, based on the 23 Spring Wheat Segment-year combinations in the study. The levels at which these correlation coefficients were significant are indicated in parentheses.

There was no significant correlation between the spectral variable F_{max} (the maximum GRABS amplitude) and any of the temporal variables. For example, there was no statistical evidence to say that maximum amplitude is linearly related to the date on which the maximum occurs. This result denies support to any hypothesis which asserts that the relative earliness or lateness of a crop's development (measured by T_{max}, T_b, and T_a) affects the value of its GRABS spectral peak. Similarly, the spectral peak value can not be said to be affected by the relative length of the growing season (measured by $T_{max} - T_b$ and $T_a - T_b$).

Highly significant correlations were observed between T_{max} and T_b and between T_{max} and T_a. That is, the relative earliness (or lateness) of the GRABS peak was associated with relative earliness (or lateness) of both first detectability and harvest. In addition, the two variables measuring the length of the growing season, $T_{max} - T_b$ and $T_a - T_b$, were highly correlated with each other and with T_a. Thus, an increase (or decrease) in the length of the growing season was associated with a later (or earlier) harvest. Remember that these results were for spring wheat segments only, and that winter wheat results could be significantly different.

1.4.2 RELATIONSHIP OF TEMPORAL-SPECTRAL VARIATION TO METEOROLOGICAL VARIATION

Each of the spectral and temporal variables described in Section 1.3.5, F_{max}, T_{max}, T_b, T_a, $T_{max} - T_b$, $T_a - T_b$, was used as a dependent variable in a series of multiple linear regression analyses, in which meteorological variables, described in Section 1.3.6, were the independent variables. These regression analyses were performed on Spring Wheat data only. Three different sets of independent variables were used to construct three different regression models for each dependent variable. The sets of independent variables used were:

A. P1, P2, P3, $(P1 + 4)^2$, $(P2 + 3)^2$, $(P3 + 3)^2$, $(P1 + P2 + 6)^2$, $(P1 + P2 + P3 + 8)^2$

B. TX(JF), TX(FH), TX(HM), TX(MD), P2, P3, P2 x TX(JF), P3 x TX(FH)

C. PR(PJ), PR(HM), PR^2(PJ), TX(JF), TX(FH), TX(HM), TX(MD), TX^2(MD), PR(HM) x TX(HM).

Model A was constructed totally from precipation variables. Since the variables P1, P2, and P3 were expressed as departures from normal precipitation, they frequently had negative values. Thus, it was appropriate to add a constant to each of them before generating quadratic terms, so that the linear models constructed would express quadratic relationships between the dependent variables and the magnitudes of the precipitation variables, unconfounded by the symmetry of the quadratic function. For example, P1 could take the values -2 and +2, both of which would yield the same value when squared. But the value +2 represented an increase of 4 inches of accumulated precipitation over the value -2, and these values had to be distinguished in order to detect a quadratic relationship between P1 and, say, T_{max}. The new variable P1 + 4 was never negative, and so this problem was avoided.

Model B was based on average daily maximum temperatures between successive biostages from planting through dough. Biostage dates were estimated using Robertson's Biometeorological Time Scale (BMTS).

Model C was based on Feyerherm's yield model for spring wheat.* The idea behind using this model was that meteorological variables identified as having a significant effect on yield could also affect temporal and/or spectral variables.

Table 1.11 presents the squared multiple correlation coefficient (R^2) values and their significance levels for each of the three models for each temporal and spectral variable. Only four of the models were statistically significant, and these were:

1. $T_{max} = 427.38 + 42.448P2 - 56.333P3 - .33315TX(JF) + .94811TX(FH) - .76843TX(HM) - 2.7197TX(MD) - .54421P2xTX(JF) + .73464P3xTX(FH)$.
   (Model B, $R^2 = .71$)

2. $T_{max} = -2059.1 + 10.488PR(PJ) - 71.349PR(HM) - .96144PR^2(PJ) + .70564TX(JF) + .17379TX(FH) - .75192TX(HM) + 54.703TX(MD) - .33611TX^2(MD) + .84406PR(HM) \times TX(HM)$. (Model C, $R^2 = .78$)

3. $T_b = 158.07 + 4.6093P1 - 8.7092P2 + 8.8562P3 - .73647(P1 + 4)^2 + .37993(P2 + 3)^2 - 1.4725(P3 + 3)^2 - .086129(P1 + P2 + 6)^2 + .26123(P1 + P2 + P3 + 8)^2$
   (Model A, $R^2 = .71$)

4. $T_b = 181.92 + 1.4524P2 - 35.534P3 + .21285TX(JF) + .097026TX(FH) + .11137TX(HM) - .83948TX(MD) - .057225P2xTX(JF) + .48660P3xTX(FH)$.
   (Model B, $R^2 = .68$)

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* See Feyerherm (1979)

The significant models were examined to determine which of the meteorological variables were most important in accounting for variation in the temporal variables. The criteria for evaluating the importance of meteorological variables were: 1) the squared partial correlation coefficient between the dependent (temporal) variable and each independent (meteorological) variable, controlling for the other independent variables, and 2) the simple linear correlation coefficient between the dependent variable and each independent variable. Table 1.12 presents the results of this evaluation.

Precipitation variables were important in all statistically significant models, but the relationships between the precipitation and temporal variables were not readily understandable in cause-and-effect terms. For example, T_b, the date of first detectability, was significantly correlated with P3, the (departure from normal) precipitation from first detectability to the peak. But to say that the precipitation P3 affected the date T_b is obviously meaningless. Furthermore, this observed correlation is of no use in the prediction of T_b, since the precipitation P3 followed T_b in time. To say that either the spectral event "first detectability" or the biological event "emergence" somehow caused the subsequent precipitation is equally meaningless. Therefore, the importance of observing such correlations lies neither in their usefulness for prediction, nor in their contribution to a cause-and-effect understanding of the interrelations among the temporal-spectral, meteorological, and biological events being studied. The value of examining the correlations between temporal-spectral and meteorological variables, in cases where cause-and-effect conclusions are clearly inappropriate, lies rather in:

1) the illumination, provided by such correlations, of the measurement process itself. The procedure of averaging temperature and accumulating precipitation over selected time periods is a way of describing a continuously changing environment in terms of discrete quantities, the meteorological variables. Similarly, the acquisition of periodic Landsat views, and the subsequent curve-fitting and temporal-spectral variable extraction process, form a quantitative framework by which to monitor continuously changing spectral response characteristics. But measured variables can neither completely nor with perfect accuracy describe an observable phenomenon, and hence relationships observed among the variables can reflect the choices made in the definition of the variables as much as the underlying physical events they are intended to measure. For example, the date on which a crop canopy first becomes detectable by Landsat should, by cause-and-effect reasoning, depend on environmental conditions which preceed this date in time, and not depend on subsequent

conditions. Yet, the variable T_b is extracted from a curve which is determined from Landsat acquisitions throughout the growing season. Thus, T_b is extracted from a curve which will be affected by environmental events that succeed it in time. That is, the measurement procedure, by its design, imposes its own point of view on its object.

2) the contribution of such correlations to the formation, in the AI's mind, of a gestalt of the crop development process, as viewed by Landsat augmented with ancillary data. The AI must decide, based on some selection of Landsat and other data covering some time period, what crop label to assign to a particular target in a scene. The decision is not made according to a set of inflexible rules, but depends on the AI's ability to evaluate the current data based on an understanding of crop dynamics, agricultural practices, the characteristics of the measurement process, the statistical nature of temporal-spectral variability, and the relationships among the available measured variables. The AI's understanding can be enhanced by the mental construction of a single unified view of the entire configuration of separate bits of information and the relationships among them. The imposition of the conventions of temporal succession and cause-and-effect upon such a unified view could obscure rather than clarify the essential data interrelationships.

The above considerations notwithstanding, there were several observed correlations in which the temporal succession of the variables was consistent with a cause-and-effect interpretation. Table 1.13 lists all instances of significant simple correlation between a temporal or spectral variable and a meteorological variable. Table 1.14 translates the symbols of Table 1.13 into words. That is, Table 1.14 lists those meteorological quantities which showed significant simple correlation with each of the temporal and spectral quantities extracted from the fitted temporal-spectral profiles. A plus (+) sign on this table indicates positive correlation; an asterisk (*) indicates temporal succession consistent with cause-and-effect. Figures 1.2 and 1.3 display calculated simple linear regression relationships for two of the significant correlations.

The regression analyses performed for this task and summarized in Tables 1.12, 1.13 and 1.14 offered no startling insights into the meteorological mechanisms underlying a crop's spectral response pattern variability. However, two general types of relationships appeared consistently throughout the results. These were 1) a positive correlation between precipitation and temporal variables. That is, increased precipitation coincided with later occurrence of spectral biostages and increased length of growing season; and 2) a negative correlation between temperature and spectral-temporal variables. That is, increased average temperature coincided with earlier occurrence of spectral biostages and with lower maximum GRABS value. Again, remember these results are for spring wheat only.

1.5 AREAS FOR CONTINUED RESEARCH

This task has produced a quantitative description of the year-to-year variation in the temporal and spectral features of wheat. The main value of this description for the AI, whose task is to label crops in a Landsat scene, lies in its use for calibrating labeling guidelines to the specific segment-year being analyzed. Therefore, a logical task to follow upon the results of the present task would be to develop consistent analyst procedures for performing site specific calibration of wheat labeling guidelines.

Analyses similar to those performed in this task would be of value in addressing the multi-crop labeling problem. Specific questions could deal with:

1) the relative magnitudes of crop-to-crop and field-to-field within-crop variability within a given segment-year. This question bears directly on the issue of crop temporal-spectral separability within a segment. This is, the AI's ability to distinguish among two or more crops in a segment depends on the extent to which the measured values of the crops' distinguishing temporal-spectral features from separate statistical populations.

2) the relative magnitudes of crop-to-crop and year-to-year within-crop variability when crop temporal-spectral values are averaged over a segment-year. This question addresses the issue of year-to-year variation in crop temporal-spectral separability. That is, labeling guidelines based on distinguishing temporal-spectral features have to be calibrated to a specific segment-year combination. The AI's ability to perform this calibration depends on an understanding of how crop differences vary from year to year.

3) crop versus year interaction. An extension of 2), this question deals with the ways in which temporal-spectral relationships among crops vary from year to year in conjunction with changes in the growth environment. It may be possible to identify environmental (e.g. meteorological) variables which affect crop temporal-spectral separability.

4) the relative magnitudes of crop-to-crop and segment-to-segment within-crop variability over a particular agricultural region. This question, as well as 2) above, is important for the calibration of labeling guidelines to a specific segment-year.

Another area for further research is the application of curve-fitting (descriptive spectral crop calendar generation) and studies of temporal-spectral variability to questions of segment size and sampling rates; that is, to basic inventory system design questions. For example, the rate at which fields should be sampled within each segment could be

affected by the relative magnitudes of crop-to-crop and field-to-field within-crop variability (see 1) above). Similarly, the rate at which segments should be sampled within a region could be affected by the relative magnitudes of crop-to-crop and segment-to-segment within-crop variability (see 4) above).

1.6 SUMMARY

A standard method for representing crop temporal-spectral response that was consistent among segments and years was developed in order to reliably measure and quantitatively describe year-to-year variation for the analyst. The method used discrete Landsat acquisitions to estimate a continuous function which represented a crop's spectral response pattern over its growing season. This method generated a consistent framework within which comparisons of temporal-spectral response characteristics among years, segments, and crops could be carried out. (See Section 1.3.4.).

Within any particular segment, the year-to-year variation in temporal-spectral response characteristics was in general highly significant relative to field-to-field variation. This observation underscored the need for the AI to calibrate labeling guidelines to the segment and year being analyzed. Table 1.7 summarizes both the observed year-to-year within-segment variation and the among segment-year variation in a useful way for the AI. (See Sections 1.4.1 and 1.4.1.1.)

The nature and magnitude of field-to-field temporal-spectral variability, within each segment-year combination, was examined and statistically tested for year-to-year consistency. In one third of the cases, the field-to-field variation was found to be not constant from year to year. A summary of the observed field-to-field variation is presented in Table 1.9. (See Section 1.4.1.2.)

Using Spring Wheat data only, all pairs of temporal and spectral variables were examined for significant correlation. There was no significant correlation between the spectral variable F_{max} (maximum GRABS amplitude) and any of the temporal variables. However, there were observed highly significant correlations among some of the temporal variables. (See Section 1.4.1.3 and Table 1.10.)

Multiple linear regression analyses were performed on Spring Wheat data, using temporal and spectral variables as dependent variables, and precipitation and temperature variables as independent variables. The multiple regression models themselves offered little insight into the causal mechanism linking meteorological factors to spectral response pattern variation. However, two general types of relationships appeared consistently throughout the results. These were 1) a positive correlation between precipitation and temporal variables; and 2) a negative correlation between temperature and spectral-temporal variables. (See Section 1.4.2 and Table 1.14.)

Table 1.1

Comparison of R^2 values between
(A) Curve-fitting by logarithmic transformation and SPSS least squares linear regression program, and
(B) Curve-fitting by nonlinear least squares program VARPRO.

Segment 1602

1975			1976			1977		
Field	A	B	Field	A	B	Field	A	B
SMGR 1	.93	.95	1	.84	.92	1	.88	.83
SMGR 2	.56	.73	2	.71	.94	2	.74	.92
SMGR 3	.74	.94	3	.77	.91	3	.93	.97
SMGR 4	.74	.78	4	.54	.71	4	.79	.74
SMGR 6	.91	.75	5	.63	.61	5	.71	.75
SMGR 7	.67	.78	6	.77	.89	6	.84	.87
SMGR 8	.68	.60	7	.77	.95	7	.78	.94
SMGR 10	.52	.63	8	.69	.87	8	.86	.97
SMGR 11	.74	.88	9	.75	.85	9	.71	.91
SMGR 12	.43	.74	10	.81	.88	10	.79	.87
			11	.70	.89	11	.84	.94
Mean	.69	.78	12	.73	.94	12	.76	.86
Std.Dev.	.16	.12	13	.70	.87	13	.80	.96
Range	.43-.93	.60-.95				SP1	.84	.94
			Mean	.72	.86	SP4	.84	.97
			Std.Dev.	.08	.10	SP6	.71	.95
			Range	.54-.84	.61-.95	SP7	.80	.96
						SP8	.64	.67
						SP9	.46	.69
						SP10	.85	.97
						SP11	.73	.69
						SP14	.66	.89
						Mean	.77	.88
						Std.Dev.	.10	.10
						Range	.46-.93	.67-.97

Table 1.2

Segment-Year Average Temporal-Spectral Variables

		F_{max} mean	F_{max} std.dev.	T_{max} mean	T_{max} std.dev.	Number of Fields
Spring Wheat						
1602	75	17.42	10.95	194.74	8.48	7
	76	22.29	4.27	190.06	4.31	13
	77	27.12	5.16	181.71	5.20	18
1616	75	36.62	7.79	195.59	3.87	15
	76	19.15	3.80	185.04	5.95	13
	77	45.41	10.69	179.88	2.79	11
1619	76	23.18	5.59	172.57	7.31	15
	77	12.43	6.87	196.83	13.34	5
	78	20.87	6.56	190.62	8.79	13
1637	75	27.42	4.67	196.51	8.47	13
	76	20.67	5.10	181.00	5.63	12
	77	31.43	8.32	179.85	7.64	14
	78	25.50	7.79	195.93	9.72	9
1652	76	26.94	13.42	178.02	5.62	13
	77	12.98	8.09	180.09	5.79	20
1677	75	21.54	6.53	165.29	6.85	15
	76	5.71	2.53	159.83	6.51	7
	77	22.00	7.21	165.68	8.10	14
	78	18.39	6.81	193.50	6.52	7
1686	75	19.20	8.11	161.74	14.44	8
	76	10.56	3.14	165.29	2.93	4
	77	6.22	2.97	163.95	9.25	11
	78	10.54	6.95	200.16	8.54	13
Mean		21.03		181.47		
Winter Wheat						
1175	76	18.00	4.21	95.55	7.40	9
	77	22.75	5.62	93.32	3.74	9
	78	28.94	7.09	119.63	2.58	15
1851	76	20.24	5.25	126.00	4.88	13
	77	23.22	8.38	129.36	3.74	14
1242	76	15.58	5.49	55.58	10.16	15
	77	23.02	12.77	70.17	17.92	8
Mean		21.68		98.52		

F_{max} = maximum GRABS value

T_{max} = Julian date of maximum GRABS

Table 1.2 Continued

Segment-Year Average Temporal-Spectral Variables

		T_b		T_a		$T_{max} - T_b$		$T_a - T_b$	
		mean	std.dev.	mean	std.dev.	mean	std.dev.	mean	std.dev.
Spring Wheat									
1602	75	158.54	13.51	233.50	6.94	36.20	6.66	74.96	14.15
	76	153.11	3.08	229.61	8.46	36.95	4.29	76.50	8.89
	77	145.51	8.08	220.59	6.31	36.20	4.66	75.08	10.40
1616	75	167.93	3.82	224.63	4.86	27.66	1.21	56.70	3.90
	76	150.92	5.65	221.44	6.62	34.12	1.64	70.52	3.63
	77	141.93	3.67	220.28	3.79	37.73	1.71	78.35	4.79
1619	76	133.90	11.59	214.07	15.10	38.40	10.11	80.17	21.99
	77	128.73	15.66	285.89	24.76	73.12	16.45	157.16	37.29
	78	144.94	2.81	240.40	17.42	45.68	7.70	95.46	16.44
1637	75	158.48	12.68	237.32	4.65	38.03	4.76	78.84	9.64
	76	148.73	3.80	217.39	6.40	31.81	4.34	68.66	4.30
	77	140.12	7.10	224.61	11.85	40.56	5.38	84.49	11.00
	78	154.94	2.94	245.80	13.33	43.65	6.48	90.86	14.36
1652	76	146.85	5.99	211.16	6.33	31.17	2.34	64.31	11.19
	77	150.90	7.34	211.04	10.55	29.19	6.69	60.14	13.89
1677	75	132.51	13.03	200.58	5.64	32.78	7.25	68.07	15.49
	76	135.00	8.43	186.15	11.50	24.83	7.18	51.15	15.25
	77	122.51	12.53	213.24	12.43	43.17	8.83	90.73	19.32
	78	140.80	8.42	251.82	19.37	52.70	11.87	111.02	25.95
1686	75	123.57	17.66	207.90	11.09	40.27	4.84	84.33	10.68
	76	138.35	2.68	193.79	4.72	26.94	2.04	55.44	4.99
	77	114.88	8.62	226.27	8.70	52.97	4.50	111.39	17.96
	78	147.80	15.04	256.74	21.65	52.36	15.06	108.94	32.94
Mean		142.65		224.97		39.41		82.32	
Winter Wheat									
1175	76	40.87	11.56	165.36	3.46	54.68	4.61	124.49	13.02
	77	39.22	3.57	162.10	7.45	54.10	3.37	122.88	8.60
	78	77.86	8.65	167.36	8.61	41.77	7.12	89.50	16.37
1851	76	90.61	6.32	165.16	5.30	35.39	3.33	74.55	7.00
	77	79.57	4.21	186.83	5.85	49.79	3.24	107.26	7.04
1242	76	11.24	8.62	139.48	9.54	49.07	4.62	128.24	16.77
	77	31.06	7.12	149.84	8.38	51.39	3.95	118.78	11.20
Mean		52.92		162.30		48.03		109.39	

T_b = Julian date on which GRABS = 2 before peak

T_a = Julian date on which GRABS = 2 after peak

Table 1.3

Summary of Weather Variables

	P1	P2	P3	PR(PJ)	PR(HM)	TX(JF)	TX(FH)	TX(HM)	TX(MD)
1602-75	- .87	5.21	3.83	7.31	.94	81.89	84.40	83.40	84.50
76	4.20	.90	- .61	1.41	.27	76.60	69.62	82.10	79.18
77	-1.90	- .21	1.44	3.49	.64	70.73	77.33	78.00	85.10
1616-75	-2.60	-1.94	.01	3.36	.40	80.44	81.78	82.40	84.09
76	-1.36	-1.66	1.26	1.82	.58	74.17	74.46	81.30	80.70
77	-3.57	-1.43	- .45	2.75	1.07	72.21	77.09	76.82	80.09
1619-76	- .99	.56	-1.75	.47	1.38	90.75	76.58	77.64	84.22
77	-3.17	1.03	.24	2.68	.35	79.00	77.75	77.40	82.80
78	4.09	-2.03	-1.99	1.98	1.61	78.42	81.00	78.90	83.40
1637-75	-1.02	1.30	2.57	3.05	.24	79.09	81.75	82.50	86.89
76	-1.42	- .44	1.29	.72	1.44	86.89	78.46	78.64	84.90
77	-3.32	- .04	- .84	2.22	.74	77.91	80.64	80.18	84.67
78	3.78	-1.43	- .20	2.19	.58	79.73	79.33	81.40	85.40
1652-76	- .14	-1.04	.37	2.40	.21	83.75	71.60	77.83	86.78
77	.33	-1.95	2.79	2.15	.02	78.31	72.62	83.10	79.18
1677-75	-3.27	1.33	- .09	3.56	.18	76.64	84.87	93.62	88.80
76	- .61	-1.26	-2.29	.72	1.24	92.62	82.27	82.20	91.00
77	-1.86	4.11	-1.60	1.66	3.23	79.82	80.90	79.82	87.44
78	5.99	1.02	2.36	4.84	.99	80.00	84.40	81.70	84.90
1686-75	-3.76	4.02	.04	3.06	0	77.50	87.13	97.86	89.60
76	-2.67	-2.09	-2.68	1.26	1.87	87.56	85.64	82.50	87.50
77	-1.42	6.05	-2.54	1.39	.78	79.83	84.67	81.82	88.00
78	1.49	.29	- .67	3.70	1.46	79.15	80.20	87.11	81.42

P1 = Accumulated departure from normal (30 year mean) precipitation from September 1 to December 31 of previous year.

P2 = Accumulated departure from normal precipitation from January 1 to T_b.

P3 = Accumulated departure from normal precipitation from T_b to T_{max}.

PR(PJ), PR(HM) = Total precipitation between planting and jointing, and between heading and milk stages.

TX(JF), TX(FH), TX(HM), TX(MD) = Average daily maximum temperature between jointing and flag-leaf, flag-leaf and heading, heading and milk, and milk and soft dough stages.

Table 1.4

Wheat Yields (bushels per acre)

Spring Wheat	County	Yield	Average	Departure
1602-75	Montrail, N.D.	24.3	26.4	-2.1
76		23.3	(1969-78)	-3.1
77		24.3		-2.1
1616-75	Cavalier, N.D.	29.1	30.1	-1.0
76		29.6	(1969-78)	-0.5
77		32.6		2.5
1619-76	Grand Forks, N.D.	30.9	32.5	-1.6
77		34.7	(1969-78)	2.2
78		36.0		3.5
1637-75	Stutsman, N.D.	26.0	25.6	0.4
76		21.6	(1969-78)	-4.0
77		25.7		0.1
78		29.9		4.3
1652-76	Stark, N.D.	25.9	24.4	1.5
77		20.7	(1969-73, 75-78)	-3.7
1677-75	Spink, S.D.	17.7	20.1	-2.4
76		6.7	(1965-78)	-13.4
77		27.5		7.4
78		17.5		-2.6
1686-75	Beadle, S.D.	14.0	17.8	-3.8
76		7.1	(1965-78)	-10.7
77		25.0		7.2
78		19.3		1.5
Winter Wheat				
1032-76	Wichita, KS	23.3	28.4	-5.1
77		23.3	(1971-78)	-5.1
78		32.0		3.6
1166-75	Lyon, KS	27.2	29.9	-2.7
76		30.5	(1971-78)	0.6
77		24.0		-5.9
1175-76	Sedgwick, KS	27.0	31.7	-4.7
77		29.7	(1971-78)	-2.0
78		32.0		0.3
1851-76	Graham, KS	32.0	31.9	0.1
77		28.7	(1971-78)	-3.2
1242-76	Canadian, OK	26.0	29.6	-3.6
77		28.5	(1975-78)	-1.1
78		32.3		2.7

Table 1.5

Temporal-Spectral ANOVA Results
Significance Levels of F-ratios for Year-to-Year Effect

Segment	Years	F_{max}	T_{max}	T_b	T_a	$T_{max}-T_b$	T_a-T_b
1602	1975-77	.01	.001	.01	.001	ns	ns
1616	1975-77	.001	.001	.001	ns	.001	.001
1619	1976-78	.01	.001	.01	.001	.001	.001
1637	1975-78	.01	.001	.001	.001	.001	.001
1652	1976-77	.001	ns	ns	ns	ns	ns
1677	1975-78	.001	.001	.01	.001	.001	.001
1686	1975-78	.001	.001	.001	.001	.001	.01
1175	1976-78	.001	.001	.001	ns	.001	.001
1851	1976-77	ns	ns	.001	.001	.001	.001
1242	1976-77	ns	.025	.001	ns	ns	ns

ns = not significant at the .05 level of significance

Anomalous Years

An anomalous year is a year in which local yield either exceeds (+) or falls short of (-) the local mean by more than one standard deviation.

Segment	Anomalous Years
1637	1976 (-) 1978 (+)
1652	1977(-)
1677	1976(-) 1977(+)
1686	1976(-) 1977(+)

Table 1.6

Year-to-Year Ranges of Temporal-Spectral Variables in GRABS units (F_{max}) or days (T-variables)

Segment	F_{max}	T_{max}	T_b	T_a	$T_{max}-T_b$	T_a-T_b
Spring Wheat (North and South Dakota)						
1602	9.70	13.03	13.03	12.91	.75	1.54
1616	26.26	15.71	26.00	4.35	10.07	21.65
1619	10.75	24.26	16.21	71.82	34.72	76.99
1637	10.76	16.66	18.36	28.41	11.84	22.20
1652	13.96	2.07	4.05	.12	1.98	4.17
1677	16.29	33.67	18.29	65.67	27.87	59.87
1686	12.98	38.42	32.92	62.95	26.03	55.95
Mean Range	14.39	20.55	18.41	35.18	16.18	34.62
Total Range (over all 23 segment-years)	39.70	40.33	53.05	99.74	48.29	106.01
Winter Wheat (Kansas and Oklahoma)						
1175	10.94	26.31	38.64	5.26	12.91	34.99
1851	2.98	3.36	11.04	21.67	14.40	32.71
1242	7.44	14.59	19.82	10.36	2.32	9.46
Mean Range	7.12	14.75	23.17	12.43	9.88	25.72
Total Range (over all 7 segment-years)	13.36	73.78	79.37	47.35	19.29	53.69

The individual segment entry under any particular variable is the range (maximum minus minimum) of the yearly segment means for that variable in that segment, as listed in Table 1.2.

The Mean Range is the arithmetic mean of the individual segment entries above it.

The Total Range is the range of all yearly segment means among all segments in the crop group (Spring or Winter Wheat).

Table 1.7

Summary of Within-Segment and Among-Segment-Year Temporal and Spectral Variation Observed in Study Segments

Description of Spectral or Temporal Variable	Summary of Observed Within-Segment Year-to-Year Ranges			Summary of Temporal and Spectral Values Among All Segment-Year Combinations			
Spring Wheat Segments	Minimum Range	Maximum Range	Mean Range	Minimum Value	Maximum Value	Overall Mean	Standard Deviation
Maximum GRABS Amplitude	9.70	26.26	14.39	5.71	45.41	21.03	9.35
Date of Maximum Amplitude (Most Active Metabolic State)	2	38	21	160*	200*	181*	13*
Date of First Crop Canopy Detection	4	33	18	115*	168*	143*	13*
Date of Harvest	0	72	35	186*	286*	225*	22*
Days from Crop Canopy Detection to Maximum ($T_{max}-T_b$)	1	35	16	25	73	39	11
Days from Crop Canopy Detection to Harvest ($T_a - T_b$)	2	77	35	51	157	82	24
Winter Wheat Segments							
Maximum GRABS Amplitude	2.98	10.94	7.12	15.58	28.94	21.68	4.30
Date of Maximum Amplitude (Most Active Metabolic State)	3	26	15	56*	129*	99*	28*
Date of First Crop Canopy Detection	11	39	23	11*	91*	53*	30*
Date of Harvest	5	22	12	139*	187*	162*	15*
Days from Crop Canopy Detection to Maximum ($T_{max}-T_b$)	2	14	10	35	55	48	7
Days from Crop Canopy Detection to Harvest ($T_a - T_b$)	9	35	26	75	128	109	20

* It should be kept in mind, when examining these statistics, that they summarize large geographic areas. (North and South Dakota for Spring Wheat, Kansas and Oklahoma for Winter Wheat.) Therefore, geographic diversity could be a significant contributor to observed variation in dates.

Table 1.8

Resulting Significance Levels from Bartlett's Test for Significant Year-to-Year Variation in Field-to-Field Within-Segment Crop Temporal-Spectral Homogeneity

	F_{max}	T_{max}	T_b	T_a	$T_{max}-T_b$	T_a-T_b
1602	.025	ns	.001	ns	ns	ns
1616	.01	.05	ns	ns	ns	ns
1619	ns	ns	.001	ns	ns	ns
1637	ns	ns	.001	.005	ns	.025
1652	ns	ns	ns	ns	.001	ns
1677	ns	ns	ns	.005	ns	ns
1686	.025	ns	.025	.025	.001	.005
1175	ns	.005	.025	.05	ns	ns
1851	ns	ns	ns	ns	ns	ns
1242	.01	ns	ns	ns	ns	ns

ns = not significant at the .05 level.

Table 1.9

Summary of Field-To-Field Within-Segment-Year Crop Temporal-Spectral Homogeneity

Temporal or Spectral Variable	Spring Wheat Segment-Years Sample Standard Deviations Minimum	Maximum	RMS*	Winter Wheat Segment-Years Sample Standard Deviations Minimum	Maximum	RMS*
F_{max}	2.53	13.42	7.19	4.21	12.77	7.17
T_{max}	2.79	14.44	7.31	2.58	17.92	7.95
T_b	2.68	17.66	9.23	3.57	11.56	7.49
T_a	3.79	24.76	11.21	3.46	9.54	7.17
$T_{max} - T_b$	1.21	16.45	7.02	3.24	7.12	4.69
$T_a - T_b$	3.63	32.94	15.51	7.00	16.77	12.19

* $RMS = \left(\sum_i df_i S_i^2 \Big/ \sum_i df_i \right)^{1/2}$ = pooled within-segment-year (field-to-field) root mean square deviation,

where S_i^2 = within-segment variance for each segment-year,

df_i = degrees of freedom corresponding to S_i^2 = number of fields - 1.

Table 1.10

Simple Linear Correlation Coefficients and their Significance Levels for Temporal and Spectral Variables, computed from 23 Spring Wheat Segment-Year Combinations

	F_{max}	T_{max}	T_b	T_a	$T_{max} - T_b$
T_{max}	.25(ns)				
T_b	.40(ns)	.71(.01)			
T_a	.00(ns)	.81(.01)	.16(ns)		
$T_{max} - T_b$	-.18(ns)	.41(ns)	-.35(ns)	.86(.01)	
$T_a - T_b$	-.22(ns)	.36(ns)	-.39(ns)	.84(.01)	1.00(.01)

Significance levels are indicated in parentheses.
ns = not significant at the .05 level.

Table 1.11

Squared Multiple Linear Correlation Coefficients (R^2)
and their Significance Levels for Multiple Linear Regression Models
to Describe Temporal-Spectral Variation in Terms of Meteorological Variation

Variable	*Model A*	*Model B*	*Model C*
F_{max}	.41(ns)	.60(ns)	.53(ns)
T_{max}	.51(ns)	.71(.01)	.78(.025)
T_b	.71(.01)	.68(.025)	.51(ns)
T_a	.32(ns)	.50(ns)	.55(ns)
$T_{max}-T_b$	.38(ns)	.44(ns)	.29(ns)
T_a-T_b	.38(ns)	.42(ns)	.25(ns)

Significance levels are indicated in parentheses.

ns = not significant at the .05 level.

Table 1.12

Important Meteorological Variables Extracted from Statistically Significant Multiple Linear Regression Models

Dependent Variable	Model	Independent Variable	P^2	r
T_{max}	B	P3	.293	.51
		TX(MD)	.303	-.60
		P3 x TX(FH)	.317	.53
T_{max}	C	PR(PJ)	.168	.46
		TX(MD)	.165	-.60
		$TX^2(MD)$	.176	-.61
T_b	A	P2	.213	-.49
		P3	.163	.55
		$(P1+4)^2$	.197	.22
T_b	B	P3	.138	.55
		P3 x TX(FH)	.165	.55

P^2 = squared partial correlation coefficient between each independent (meteorological) variable and the dependent (temporal) variable, controlling for other independent variables.

r = simple linear correlation coefficient.

Table 1.13

Meteorological Variables that showed Significant Correlation with Temporal and Spectral Variables in Spring Wheat Segments

Temporal or Spectral Variable	Meteorological Variable	Correlation Coefficient	Level of Significance
F_{max}	TX(JF)	-.42	.05
T_{max}	P1	.47	.05
	P3	.51	.05
	$(P1+4)^2$	.44	.05
	$(P3+3)^2$	.44	.05
	P3 x TX(FH)	.53	.01
	PR(PJ)	.46	.05
	TX(MD)	-.60	.01
	TX^2(MD)	-.61	.01
T_b	P2	-.49	.05
	P3	.55	.01
	$(P2+3)^2$	-.48	.05
	$(P3+3)^2$	.50	.05
	P2 x TX(JF)	-.48	.05
	P3 x TX(FH)	.55	.01
	TX(MD)	-.47	.05
	TX^2(MD)	-.47	.05
T_a	TX(MD)	-.43	.05
	TX^2(MD)	-.44	.05
$T_{max}-T_b$	$(P1+P2+6)^2$	.42	.05

Table 1.14

Summary of Significant Correlations of Temporal-Spectral Variables with Weather Variables in Spring Wheat Segment-Years

Temporal and Spectral Variables		Correlated Meteorological Variables
maximum GRABS value	*	average daily maximum temperature from jointing to flag-leaf
date of maximum GRABS	+*	precipitation from Sept. 1 to Dec. 31 of previous year
	+*	precipitation from first detectability to peak
	+*	precipitation from planting to jointing
	+*	average daily maximum temperature from flag-leaf to heading
		average daily maximum temperature from milk to dough
date of first detectability	*	precipitation from Jan. 1 to first detectability
	+	precipitation from first detectability to peak
		average daily maximum temperature from jointing to flag-leaf
		average daily maximum temperature from flag-leaf to heading
		average daily maximum temperature from milk to dough
date of harvest	*	average daily maximum temperature from milk to dough
number of days between first detectability and peak	+*	precipitation from Sept. 1 of previous year to first detectability

* indicates correlations in which the temporal succession of the meteorological and temporal or spectral variable is consistent with a cause-and-effect interpretation.

\+ indicates a positive correlation.

absence of + indicates negative correlation.

Figure 1.1

Location of Study Segments

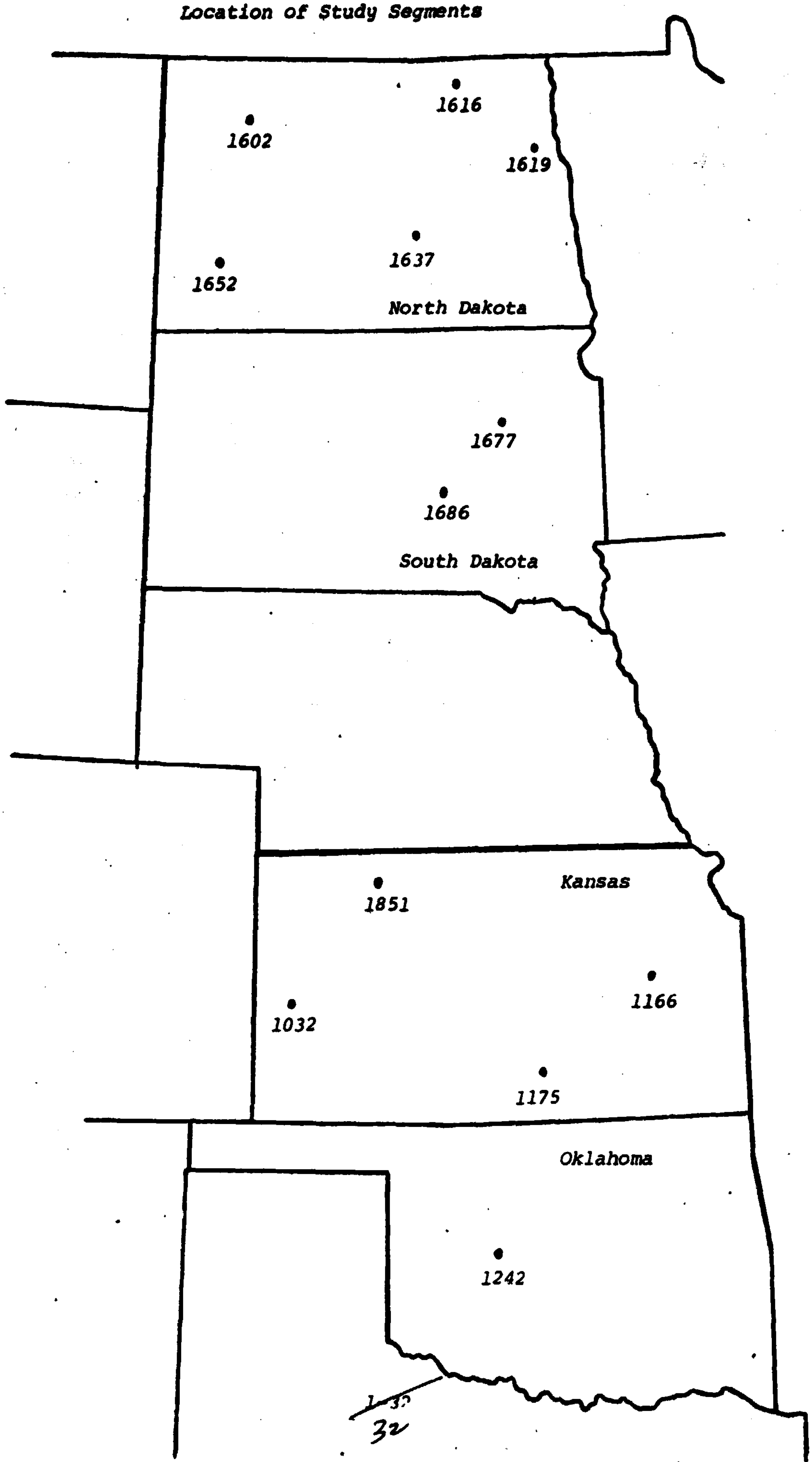


Figure 1.2
T_{max} versus TX(MD)

23 Spring Wheat Segment - Years

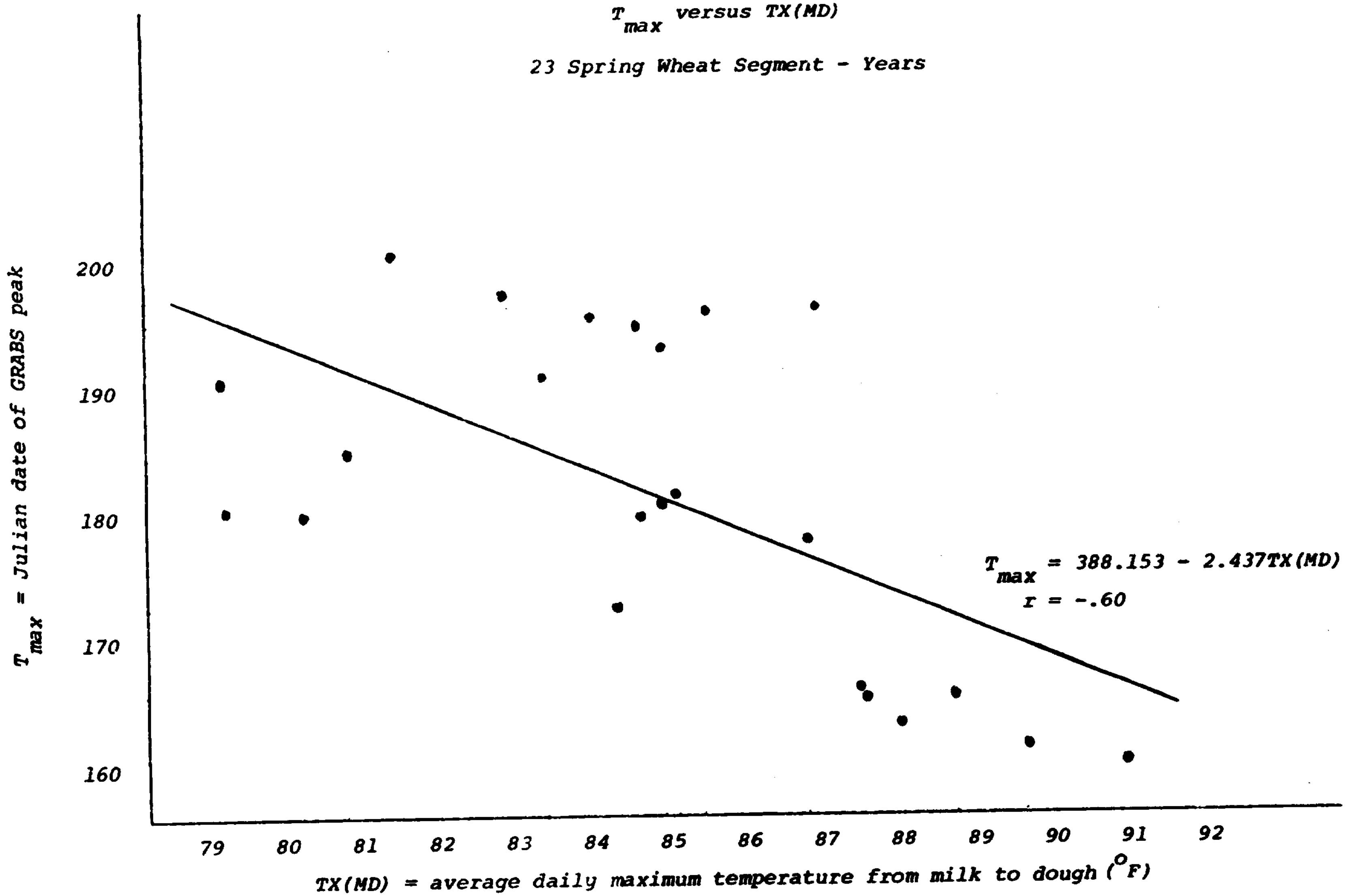
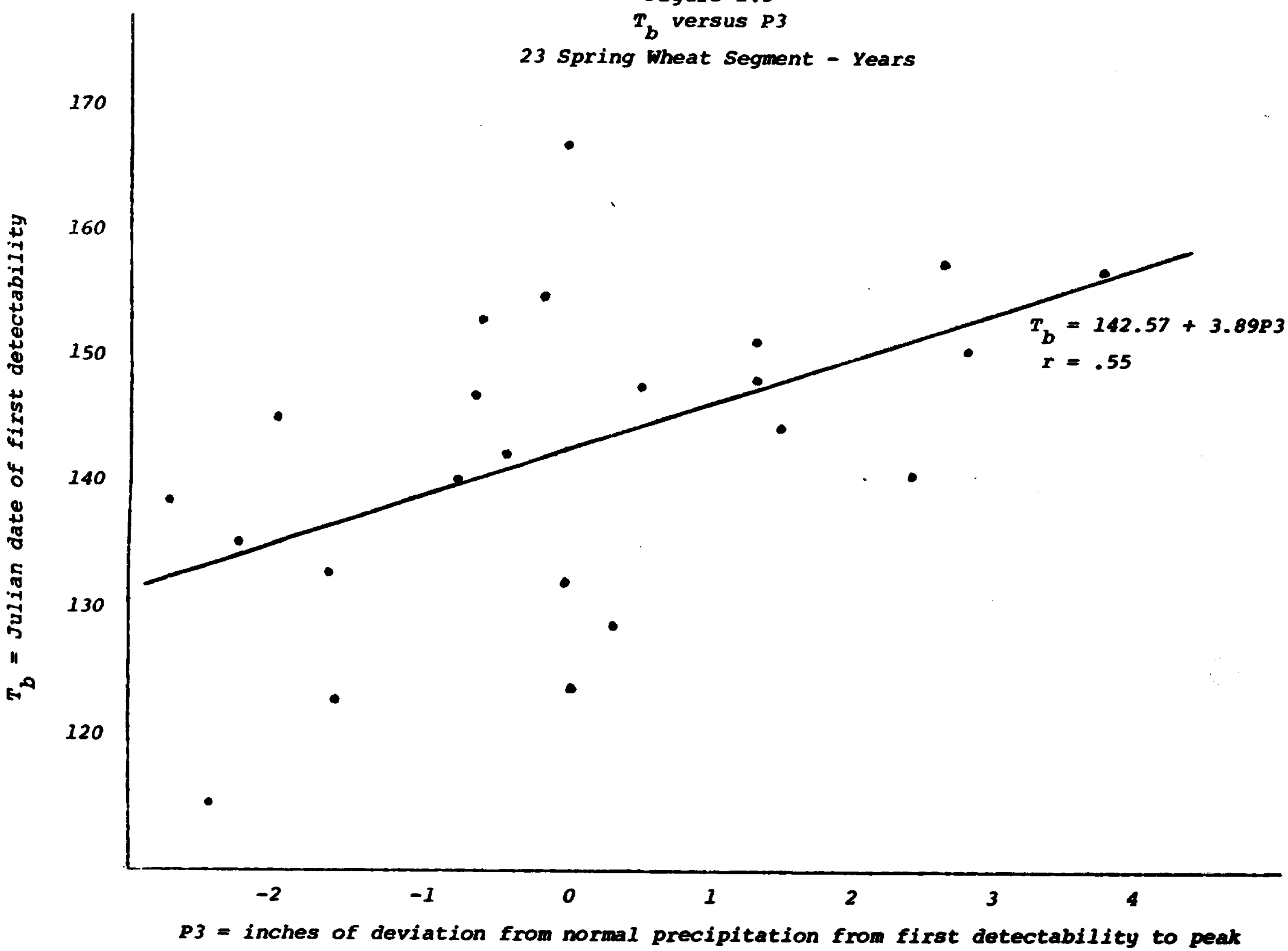


Figure 1.3

T_b versus P3

23 Spring Wheat Segment - Years



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TASK II: AI GUIDELINES FOR

CORN AND SOYBEANS

by

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2.0 Task II: AI Guidelines for Corn and Soybeans

2.1 INTRODUCTION

During the development of the LACIE system and the associated technology for agricultural resource information extraction, the AI labeling procedures have been consistently improving. New and improved quantitative data presentation formats (such as trajectory and spectral plots, high contrast - high stability imagery, etc.) have been developed and are presently being utilized. Machine analysis procedures such as Procedure 1 and the UCB Delta Function Stratification Procedure have been developed. These developments have been primarily directed at alleviating and simplifying the analyst-machine interface and allowing the analyst to concentrate on his primary task, which is labeling.

The LACIE development was concentrated primarily on the analysis for wheat and the separation of wheat and non-wheat. The multicrop program for FY79-80 requires that this technology be extended to other crop types with the initial emphasis on corn and soybeans. This task is intended to continue the development of AI guidelines for the labeling of corn and soybeans and the development of analysis procedures which were initiated during FY78.

2.2 OVERALL OBJECTIVE AND APPROACH

The overall objective of this task was to develop improvements to current AI labeling technology. Two areas within the technology which were emphasized for development were: 1.) improvements to a priori information in the form of definitive AI labeling guidelines for corn and soybeans, and 2.) improvements to crop identification Landsat data analysis techniques or procedures. In order to address these two areas of emphasis three subtasks were identified. Subtask A: Corn and Soybeans Labeling Guidelines was to address objectives relative to the first area of needed development.

The overall objective of Subtask A was to evaluate and further develop as necessary the first-generation corn and soybeans AI labeling guidelines that were developed in the FY78 contract year. The first-generation corn and soybeans guidelines were developed with pre-existing LACIE blind sites which were not centralized within the Corn Belt. The use of the LACIE data was necessary since adequate central Corn Belt data was not

available in FY78. The testing of the guidelines, however, was on crop-year 1978 corn and soybean data specifically gathered for the corn-soybean studies. The results of the testing of the guidelines as well as the more central Corn Belt data set were to be used to determine needed modifications to the first generation Corn-Soybeans Labeling Guidelines.

Subtask B: Extension of Delta Function Stratification (DFS) Procedure to Corn and Soybeans, and Subtask C: Advanced Spectral Aids and Procedures for Multicrop were to address objectives relative to the second area of needed development. The overall goal of Subtask B was to evaluate and refine the UCB-Delta Function Stratification (DFS) procedure for multicrop situations in general. DFS was originally developed during LACIE, and small grains were emphasized during that development phase. Thus it was desired to extend and evaluate the DFS procedure relative to summer crops (corn and soybeans) and multicrop in general, as well as refine some procedural aspects of the method.

When trying to differentiate between closely similar crop types as between crop types within the same crop group (e.g. wheat vs. barley within small grains, or corn versus sunflowers within summer crops) subtle temporal-spectral differences become significant. In order to effectively examine the differences, the analyst must carry out his analysis in an orderly and logically consistent manner. And because of the increased need for sophisticated spectral aids and data presentation, the analysis procedure must be efficient in order to properly access all the relevant data. Thus the overall goal of Subtask C was to develop analysis techniques or procedures for crop identification with Landsat that would allow the efficient and effective processing of the data by the analyst as well as for a smooth interfacing of analyst and machine processing.

2.3 SUBTASK A: CORN AND SOYBEAN LABELING GUIDELINES

2.3.1 OBJECTIVE

The objective of this subtask was to continue and complete for at-harvest the development corn and soybean AI labeling guidelines. The 1978 data set was expected to provide better acquisition histories for high density summer crop regions (Corn Belt) than was available for the first-generation guideline development in the previous contract year. In addition, the 1978 data set provided a different set of segments so that testing of the initial guidelines would be independent of the data set used to develop the initial guidelines.

2.3.2 APPROACH

Experimental Design Multicrop Interpretation Test

In order to (1) establish baseline summer crop accuracy levels with the first-generation guidelines and (2) determine problem situations for which current guidelines were inadequate, an interpretation test for corn, soybeans, and major confusion crops was designed and administered to a group of UCB analysts.

The entire test consisted of ten segments and seven analysts, each analyst interpreting five segments. From this full set of 35 interpretations, a subset of 21 interpretations was selected and arranged to form a symmetric balanced incomplete block (SBIB) design. This design featured seven of the ten segments and all seven analysts, each analyst interpreting three segments. The first two of the five interpretations by each analyst were excluded from the design to allow for familiarization with the guidelines, the spectral aids, the test regions, and the types of responses required by this test. The design layout is given in Table 2.1.

		Analysts (Treatments)						
		A	B	C	D	E	F	G
	241	x		x			x	
	824		x				x	x
	854			x		x		x
Segments	883				x	x	x	
(Blocks)	886	x	x			x		
	1572	x			x			x
	1591		x	x	x			

Table 2.1 Interpretation Test Design Layout

The experimental design model and ANOVA table used were:

$$Y_{ij} = \mu + b_i + t_j + e_{ij}\ ;\ i = 1,\ldots,7;\ j = 1,\ldots,7;$$

where Y_{ij} is the variable of interest (e.g. percent correct, commission error, etc.) measured for the i^{th} segment and j^{th} analyst, if that combination is marked by an X in the above table; μ is the overall mean; b_i is the effect due to segment i, and $\Sigma b_i = 0$; t_j is the effect due to analyst j, and the t_j are independent, identically distributed $N(0,\sigma_t^2)$; and e_{ij} are independent $N(0,\sigma^2)$ residuals. The model assumes that there is no interaction between segments and analysts.

ANOVA

Source of Variation	Sum of Squares	Degrees of Freedom	F-ratio
Segments (unadjusted)	$S_1 = \frac{1}{3}\sum_i Y_{i\cdot}^2 - \frac{1}{21}Y_{\cdot\cdot}^2$		
Analysts (adjusted for segments)	$S_2 = \frac{1}{21}\sum_j (3Y_{\cdot j} - \sum_{i(j)} Y_{i\cdot})^2$	6	$\frac{4S_2}{3S_e}$
Analysts (unadjusted)	$S_3 = \frac{1}{3}\sum_j Y_{\cdot j}^2 - \frac{1}{21}Y_{\cdot\cdot}^2$		
Segments (adjusted for analysts)	$S_4 = \frac{1}{21}\sum_i (3Y_{i\cdot} - \sum_{j(i)} Y_{\cdot j})^2$	6	$\frac{4S_4}{3S_e}$
Residual	$S_e = S - (S_1 + S_2)$ $= S - (S_3 + S_4)$	8	
Total	$S = \sum_{ij}\sum Y_{ij}^2 - \frac{1}{21}Y_{\cdot\cdot}^2$	20	

In the above ANOVA table, $Y_{i\cdot} = \sum_j Y_{ij}$, $Y_{\cdot j} = \sum_i Y_{ij}$, $Y_{\cdot\cdot} = \sum\sum_{ij} Y_{ij}$,

$\sum_{i(j)} Y_{i\cdot}$ *represents the sum of* $Y_{i\cdot}$ *over those segments interpreted by analyst* j, *and* $\sum_{j(i)} Y_{\cdot j}$ *represents the sum of* $Y_{\cdot j}$ *over those analysts who interpreted segment* i. *Note that* $S_1 + S_2 = S_3 + S_4$: *the SBIB design allows two separate but complementary analyses so that the effect of analysts could be tested for significance after adjusting for segment effect, and the effect of segments could be tested after adjusting for analyst effect.*

Should a particular analysis indicate a significant segment or analyst effect, specific relationships among segments or analysts could be tested using Scheffé's multiple comparisons procedure. The

procedure described below applies to segment effects, but the procedure for analyst effects is analogous. First, adjusted estimates of the b_i, the segment effects, are given by the formula $\hat{b}_i = \frac{3}{7}(Y_{i\cdot} - \frac{1}{3} \sum_{j(i)} Y_{\cdot j})$. To test the hypothesis H_0: $C = c_1 b_1 + c_2 b_2 + \ldots + c_7 b_7 = 0$ (for constants c_i such that $\sum_i c_i = 0$) against the alternative H_a: $C \neq 0$ at the α level of significance, the estimate $\hat{C} = c_1 \hat{b}_1 + c_2 \hat{b}_2 + \ldots + c_7 \hat{b}_7$ is compared with the critical value $K = (\frac{18}{7} \hat{\sigma}^2 F_{\alpha,6,8} \sum_i c_i^2)^{1/2}$, where $\hat{\sigma}^2$ is the Residual Mean Square from the ANOVA and $F_{\alpha,6,8}$ is a tabulated value from the F distribution. If $-K < \hat{C} < K$, H_0 is accepted; otherwise H_a is accepted. Specific relationships among the b_i can be tested by the proper choice of the c_i. For example, to test whether segment 1 is significantly different from the mean of all other segments, the appropriate c_i would be $c_1 = 6$, $c_2 = c_3 = \ldots = c_7 = -1$. If H_a is accepted, segment 1 would be judged significantly different from the others.

The overall experimental design (all five interpretations by each analyst) allowed for a test of learning effect: four of the test segments that were first interpretations of one analyst were also last interpretations of another analyst. Thus, if analyst effect were found to be not significant, a t-test of the paired observations (first versus last) could be performed to test whether the interpretation of these segments showed improvement over the course of the experiment.

Test Data Set

The test data set was drawn from a set of eight LACIE Transition wheat segments and fifteen 1978 high density corn and soybean segments that were available at UCB when the test was designed. The JSC analysts had previously determined that the wheat segments had a significant proportion of corn and/or soybeans for testing. The candidate segments were screened for adequacy of acquisitions, freedom from cloud cover, and availability of ancillary data. Ten test segments were finally selected:

three LACIE transition segments, the only three that passed the screening, and seven corn and soybean segments which were drawn at random. These ten segments are listed in Table 2.2 and the order of segments interpreted by each analyst is listed in Table 2.3.

The seven analysts who participated in the test were UCB personnel, some of whom were drawn from other projects. All but one of the AI's (analyst interpreters) were experienced agricultural remote sensing analysts, although the degree of familiarity with LACIE-like procedures and data products varied. A training session was held prior to the start of testing in order to help standardize the experience level of the analysts and also to familiarize them with the guidelines being tested.

Table 2.2 Multicrop Interpretation Test Segments

	Segment #	Location
1.	886	Pottawatamie, Iowa
*2.	1075	Howard, Nebraska
3.	185	Traverse, Minnesota
4.	241	Deuel, South Dakota
*5.	1572	Custer, Nebraska
*6.	1591	Webster, Nebraska
7.	145	Warren, Iowa
8.	824	Iroquois, Illinois
9.	854	Tippecanoe, Indiana
10.	883	Palo Alto, Iowa

* LACIE Transition wheat segments

Table 2.3 Test Segments Interpreted by Each Analyst

Analyst	*Segments* (in Order of Interpretation)*				
A	*2*	*3*	*1*	*4*	*5*
B	*7*	*2*	*6*	*1*	*8*
C	*3*	*7*	*4*	*6*	*9*
D	*8*	*3*	*5*	*10*	*6*
E	*5*	*7*	*10*	*9*	*1*
F	*9*	*2*	*8*	*4*	*10*
G	*10*	*4*	*9*	*8*	*5*

* *Numbers refer to segments listed in Table 2.2*

The standard data set for each segment consisted of: (1) PFC Landsat image products 1 and 3 for all available acquisitions, (2) a hardcopy image of a temporal class stratification generated from a linear combination of GRABS values across selected summer acquisitions (see Task II, Subtask B for a description of the pixel-by-pixel Delta Function Stratification (PXP-DFS) procedure), (3) a three pixel-by-three-pixel numeric block dump of Tasseled Cap Brightness (TC1), GRABS (TC2 - a soil threshold) and 2 x MSS7/MSS5 (7/5 VI) values for selected acquisitions centered on the 209 sample pixels, (4) plots of GRABS versus time for the 209 sample pixels, and (5) unitemporal scatter plots of GRABS versus TC1 for pixels within the summer crop strata derived from the PXP-DFS procedure. All numeric data were sun angle and haze corrected.

In addition to the Landsat data listed above, analysts were provided with information manuals containing: (1) the first generation corn-soybeans, summer crop guidelines, (2) crop phenological and cropping practices information, (3) general background materials on the Great Plains and Corn Belt, (4) state-specific environmental information (geology, climate, etc.), (5) statewide long-term average and year-specific crop calendars based on ESCS data, and (6) historical county crop statistics (last three available years). Other ancillary data included 1:250,000 USGS topographic maps, county soil surveys, and state crop and weather bulletins issued weekly by the ESCS.

In addition to the data listed above which was standardly made available for each test segment, the analyst was free to generate any additional spectral aids that he thought might be of value to him.

Test Administration

The test was administered in the following manner: (1) The analysts were familiarized with the labeling guidelines, data products, and suggested interpretation approaches during an initial training session. The analysts were instructed to review background materials on summer crops and on the general environments of the Great Plains and Corn Belt before starting the interpretation of individual segments. (2) Then for each test segment the analysts were required to perform the following three steps:

(A) Review segment-specific ancillary data.

(B) Label, relative to a specific reference date, each of the 209 sample pixels pure or mixed.

(C) Assign each sample pixel to the appropriate crop group land use class (summer crops, winter small grains, spring small grains, alfalfa/pasture/range, idle, or non-agricultural).

Due to the temporal misregistration between acquisitions, it was necessary to specify a given acquisition for each segment as a reference date. The analyst then labeled the 209 sample pixels relative to their location on that reference date, even if the sample pixels fell in a different location (field) on other acquisitions. Multitemporal data, however, was used for all of the interpretations. Initially the reference date had been specified to the analyst, that date being the acquisition to which the ground data was registered. However, problems soon arose in a number of segments where the specified reference date was too early in the crop season and field boundaries were lacking. This made it quite difficult for the analyst to determine in which field the sample pixel fell. Thus, after this problem was identified, analysts were allowed to select their own reference date which was more appropriate for meeting the test objectives.

(D) Identify the specific summer crop type for each summer crop group pixel identified in step (B).

(E) *Specify an alternative summer crop label or labels to the pixels from (D)).*

(F) *Assign a confidence code from 1 to 4 reflecting analyst's confidence in the summer crop type label assignments (see Table 2.4), and*

(G) *State a reason for the given label assignments.*

Pixels perceived as mixed by an analyst were assigned more than one crop/land use group label according to the number of components in the mixed pixel. The summer crop component of a mixed pixel had to be labeled further as in steps (D-G). In the interest of saving time, analysts did not have to provide the detailed information in steps (D-G) for non-summer crop group pixels.

No rigorously defined analysis procedure was specified to the analyst for use in the test; however, it was suggested that they first perform steps (B & C) for all 209 sample pixels; then make a second pass through the data in order to label summer crop pixels according to steps (D-G). Many AI's, however, found it more convenient to do all steps for each pixel in one pass, particularly for the central Corn Belt (low proportion of crop groups other than summer crops) segments. The only procedural requirement placed on the analyst was that he fully consider all labeling guidelines and data products that were in the standard set for each segment. Analysts were allowed to confer with one another in this respect during the interpretation of their first two "familiarization" segments. At the request of JSC personnel, the subsequent interpretations (three segments/analyst) were done independently.

Figure 2.1 is an illustration of the recording form used by the AI for recording his answers for steps (B-G). (See Table 2.4 for definitions of the crop and confidence codes used).

Correction of Analysts' Labels

Analyst labels were compared manually to aerial photos with ground data overlays in order to determine the correctness of each analyst's label. Pixels for which the correct label could not be determined due to ground data ambiguity were excluded from the results. No pre-judgement as to the "correct" location of a given sample pixel with respect to a field or a landscape feature was made by the test evaluator. The AI was asked to delineate on an overlay of his reference date the fields he had labeled relative

to a given sample pixel. The analysts' perception of the pixel's location and purity, if it appeared reasonable, was taken as correct when evaluating the labels. Contingency tables comparing analyst labels to ground data were drawn up for each of the five segments for each of the seven analysts. These tables are included in Appendix A for reference. In order that the total number of sample pixels for a given segment would remain the same across analysts (i.e. 209 or some subset thereof), multiple labels for mixed pixels were given fractional values (e.g. one-half or one-third) depending on the number of labels assigned to the mixed pixels.

Variables of Interest

The following variables were calculated from the corrected test results: (1) estimated proportion of segment within class of interest (based on 209 pixel sample of ground data), (2) AI proportion estimation error from estimated true proportion, (3) RMS error (across all AI's), (4) per cent correct, and (5) two different types of commission error. The definition of these variables appears in Table 2.5. These variables were calculated for each segment by:

a.) crop group/land use class (e.g. small grains-winter and spring combined, summer crop, alfalfa pasture-range, etc.)

and b.) summer crop type (e.g. corn, soybean, sunflowers, etc.)

The value of these variables for the ten test segments is contained in Appendix B.

In addition to the quantitative analyses performed on the test results, a qualitative evaluation of the results was conducted to isolate problem areas and try to understand the factors that influenced analyst label assignments. AI errors were reviewed on a pixel-by-pixel basis by an experienced analyst with respect to the available ground and spectral data. AI errors relative to the available spectral data were evaluated against Landsat data sampled by two different techniques. One procedure used a standard ten-by-ten (209) pixel sample that was used to generate the spectral aids for the test and the other procedure used a sample of field center data. The first sample was less than optimum for assessing the actual spectral distributions of summer crops since only a single pixel (often mixed or misregistered among acquisitions) was usually selected from any given field and the total number of samples was too small to adequately determine the crop's spectral distributions. Time constraints, however, did not allow additional intensive sampling of most test segments. The 209 pixel sample did, however, adequately represent the corn and soybean spectral distributions for those segments that were "wall-to-wall" corn and soybeans. The second sampling

method, field sampling, involved the selection of a contiguous group of pixels from within a given field that were determined to be pure on all acquisitions for as many summer crop fields as were large enough to be sampled. Field mean values (GRABS and TC1) were examined in addition to individual pixel values. The larger amount of information obtained through field sampling was particularly valuable in segments where several summer crops with small segment proportions were found. Based on this AI labeling error analysis and comments from AI's involved in the test, an attempt was made to distinguish between errors due to inadequate guidelines and errors arising from other sources.

2.3.3 RESULTS AND DISCUSSION

Results of the Statistical Analysis

The average values for the six variables defined in Table 2.5, obtained across all AI's and all segments, are presented in Table 2.6. These results included the segments excluded from the SBIB design in allowing for a learning effect. Combined summer crop labeling accuracy was 87.14%, with a commission error (B) of 12.58%. Labeling accuracy for corn alone was 90.64%, and accuracy for soybeans alone was 85.68%. Commission error (B) for these two crops was 12 and 8.97% respectively.

Table 2.7 contains the average values of the six variables for just the 21 analyst/segment pairs in the SBIB design. With the learning effect segments excluded, labeling accuracies for corn and combined summer crops were approximately the same as above: 90.11% and 87.94% respectively. Average soybean accuracy was slightly higher (87.47% correct) when the results from the first two interpretations for each AI were excluded from the calculations. Average commission errors were slightly lower for summer crops, corn and soybeans (11.20%, 10.01% and 7.31 respectively) when the learning effect segments were excluded.

Analyses of variance were performed for a subset of the variables described above in accordance with the symmetric balanced incomplete block (SBIB) design described in section 2.3.2. The results of these analyses are summarized in Table 2.8. Complete ANOVA tables and the computations for Scheffê's multiple comparisons test are contained in Appendix C. No analysis of variance could be performed for soybeans because two of the segments (Great Plains segments 1572 and 1591) had virtually no soybeans. This situation arose for two reasons. First, it was our desire to evaluate the labeling guidelines in a variety of diverse agricultural environments. Thus segments from areas other than the central Corn Belt were included in the test. In particular, segments 1572 and 1591 were chosen so that a potential corn/sorghum confusion could be evaluated. Second, the number of segments with adequate ancillary data was limited, and there were no available substitutes for these two Great Plains segments that would not have drastically compromised the desired level of regional diversity.

Although there was no statistically significant analyst effect in any of the ANOVAs, there were real differences in analyst perform-

ance, differences that were not measured by percent correct or commission error. These are discussed later in the qualitative evaluation section. Furthermore, the SBIB design required the assumption of no segment-analyst interaction. Violation of this assumption would increase the residual mean square and thus conceal what might be a measurable analyst effect.

For variables whose ANOVAs resulted in significant segment effects, examination of the data disclosed that performance on Segment 1591 was dramatically different from the other segments. The significance of this difference was confirmed statistically using Scheffé's multiple comparisons procedure. (For details, refer to Appendix C.) Furthermore, examination of the labeling errors made in Segment 1951 indicated that this disparate performance was due to a corn/sorghum confusion problem. Analysts' performance and apparent factors that contributed to labeling errors are discussed more fully in a following section.

Since the analyst effect was found to be non-significant, it was valid to test for a learning effect. Segments 824, 854, 883, and 1572 were each the first interpretation of one analyst and the last interpretation of another. Thus paired t-tests were carried out to see if a significant difference could be detected between results from first interpreted segments and last interpreted segments. Eleven t-tests were computed (% Correct, Commission A, Commission B and AI proportion Estimate Error separately for both corn and soybeans, and % Correct and Commission B for all summer crops combined), none of which were significant at the .05 level. Thus it was concluded that for the total group of analysts that participated in the interpretation test there was no significant effect due to a learning phenomenon. The paired t-test computations are summarized in Appendix C.

Discussion of Interpretation Problems

Five of the test segments were located in the heart of the Corn Belt: 824 (Illinois), 854 (Indiana), and 145, 883, and 886 (Iowa). These segments had similar agricultural environments in which unirrigated corn and soybeans occupied the majority of the acreage. Other crop/land use groups were only moderately represented within a segment or, in some cases, entirely absent. The overall level of labeling difficulty was relatively low. Basically, the AI only had to decide between corn and soybeans within these segments, and the large proportion of these two crops facilitated the application of the guideline directed decision logic.

The remaining five test segments were located on the periphery of the Corn Belt: 185 (Minnesota), 241 (South Dakota), and 1075, 1572, and 1591 (Nebraska). The agricultural environments of these segments differed substantially from those of the "wall-to-wall" corn and soybean segments. Not all of the five fringe area segments contained both corn and soybeans. Additional summer crops (sunflowers, sugar beets, sorghum) increased the level of labeling difficulty by requiring the AI to incorporate additional labeling criteria and label as many as four different summer crops in a segment. Larger proportions of non-summer crop groups within the segments also added

to the confusion. 185 and 241 had proportions of spring small grains that were equal to or greater than the combined proportions of corn, soybeans and miscellaneous other summer crops. Alfalfa, pasture and range occupied one-half to three-quarters of the area of the Nebraska segments, where soybeans were largely absent and the major summer crop confusion was between corn and sorghum. The variety of crop types in these segments permitted the evaluation of guidelines other than just those concerned with separating corn from soybeans.

Due to the differences between the two agricultural environments (Central Corn Belt and fringe areas) and differences in interpretation difficulty, the five Central Corn Belt segments were evaluated separately from the fringe segments. Evaluation of the results from the five peripheral Corn Belt segments was carried out to determine the consistency of the findings from the Corn Belt segments relative to other geographic areas and to evaluate the adequacy of the guidelines for separating corn and soybeans from other summer crops in addition to separating them from each other. Since the ANOVA results revealed no significant learning effect, interpretations from all segments were considered in the following evaluation of test results regardless of their position in the analysis sequence.

The Central Corn Belt Segments

Results for just the five central Corn Belt segments were calculated separately and are shown in Tables 2.9 through 2.13. The overall percent correct for all pixels labeled was 88.25%. A correctly labeled pixel means that the pixel was not only assigned to the correct land use group but within the summer crop land use group was also assigned to the correct summer crop type. Of just the corn and soybean pixels, 91.88% were correctly labeled. Of all the pixels that were labeled either corn or soybeans, 2.48% of those pixels were committed (commission error B) from other land use groups to one or the other of the two crops. Labeling accuracy for corn across the five Central Corn Belt segments was 94.2% correct, with a commission error (type B) of 8.5%. For soybeans the labeling accuracy was 89.03% correct with a commission error (type B) of 5.67%. The percent correct for corn and soybeans for individual segment interpretations ranged from 85.8% to 100% for corn and from 81.25% to 95.99% for soybeans. Appendix B contains results by individual segments. The labeling accuracies for corn and soybeans within the five Central Corn Belt segments were slightly higher than the results obtained across all ten test segments and across the seven segments included in the SBIB design. Thus it appears that the highest corn and soybean labeling accuracies can be obtained within areas where these two crops occupy most of the acreage.

Looking at what types of confusions accounted for most of the labeling error, we can see that 30.55% of the total error (11.75%) within these five segments involved confusion among specific summer crop types within the summer crop land use group, 35.23% of the total error involved confusion between summer crops as a group and the other land use groups, and 34.22% of the total error involved confusion among the other land use groups not including the summer crop land use group. (See Table 2.11).

The greatest source of confusion with summer crops as a land use group was the alfalfa/pasture/range (APR) land use group. 29.52% of the total error involved confusion between the summer crops land use group (SC) and APR land use group. This was particularly true for segment 883, where temporal and spectral similarities in the data contributed to the mislabeling of hay as corn and soybeans as alfalfa or pasture. In general, nearly equal amounts of corn (.92%) and soybeans (1.13%) were committed to the APR category. More than twice as much APR was committed to corn (.99%) as to soybeans (.43%).

Within the summer crop land use group, the greatest source of labeling error involved confusion between corn and soybeans. (See Tables 2.12 and 2.13). 61.84% of the error (3.59%) due to confusion between specific summer crops was due to committing of soybeans to corn. This problem was most apparent in segment 854, where excessive rains during the growing season resulted in standing water in the fields, uneven canopy development, and consequently unexpected soybean signatures. Corn fields incorrectly committed to soybeans accounted for most of the remaining error within the summer crop category. These remaining errors did not appear to be directly related to inadequate data separability, however, as certain analysts demonstrated a greater tendency to make these errors than did other analysts.

Errors due to confusions among the non-summer crop land use groups were not analyzed in any detail, since the objective of this task was to refine summer crop labeling guidelines. In addition, some of the non-summer crop land use groups did not occur in significant proportions within the five Central Corn Belt segments and thus could not be adequately evaluated.

When analyst labels were corrected against ground data, many of the incorrect AI labels were surprising in view of the guidelines and data that had been available. This was especially true of corn/soybean confusions within the five Central Corn Belt segments. Most corn and soybean fields appeared obvious on the PFC Product 1's alone

so that they could have been identified without referring to the numeric data. Therefore, it was necessary to determine what factors had contributed to the AI errors involving summer crops before completing the evaluation of the performance of the initial corn and soybean labeling guidelines.

Because time constraints did not permit a detailed review of all results, the error evaluation was confined to those Central Corn Belt analyst/segment combinations that had been included in the SBIB design. (See Table 2.14). Thus, results from the first two segments labeled by a given AI were not considered. It was assumed at the time that analyst inexperience with the guidelines and data products played a greater role in labeling errors in the first two segment interpretations than in the last three. Thus the last three segment interpretations by an AI were assumed to be useful for evaluating interpretation problems stemming from the summer crop labeling guidelines themselves.

Table 2.14 Central Corn Belt Test Results Used in Summer Crop Error Evaluation

Segment	Analyst		
824	B	F	G
854	C	E	G
883	D	E	F
886	A	B	E

Determination of the factors contributing to incorrect summer crop labels was made by an experienced analyst, who evaluated each error on the basis of what data was available for the use of the test analyst and the information presented in the guidelines. Other information provided by the AI such as alternate labels, confidence in label assignments, decision criteria, and comments reflecting his overall reaction to a specific segment were also

factored into the overall evaluation of the errors. Due to the simplicity of the labeling situation in the Central Corn Belt segments, the evaluation of the error factors was fairly simple and straightforward as most sources of error appeared to be fairly obvious.

The first step in the error evaluation was to establish how common each incorrect label was across AI's. An error made by a minority of analysts would indicate that the guidelines had been adequate to label the field based on available data (hence the majority labeled it correctly) and that the incorrect label was due to individual analyst error. Conversely, an error made by the majority would point toward inadequate data or guidelines. The results of this effort showed that over 58% of the summer crop errors involved fields that were mislabeled by a majority (two of two, two of three, or three of three) of the analysts. Another 25% of the errors were made by a minority (only one of three) of the AI's. The remaining errors did not reveal any clear trends in that the errors were made by only one of two analysts or by the only analyst who labeled the field. The last two situations, one of two and one of one, arose due to the fact that AI's were allowed some liberty in determining into which field a sample pixel fell.

The second step in the error evaluation was to determine the various factors that contributed to the incorrect labels. Acquisition history, cloud cover, and availability of ancillary data were not taken into account since these criteria were used to screen segments for inclusion in the test. Of the error factors listed below, 1 through 4 reflect guideline and data problems that were beyond the analyst's control, while 5 through 8 were primarily analyst related problems. The error factors determined to be operative were:

(1) a.) No apparent separation in data based on currently exploited features or b.) deficiency in initial labeling guidelines. This category of error was of most interest for this subtask. The fields that were mislabeled due to this factor were designated for further study related to definition of other features that might lead to an increase in identification accuracy or for refinement of the initial guidelines. It is recognized that temporal and spectral similarity between confusion crops might be too great to permit reliable separation. If this turns out to be the case in some situations, it would be desirable to incorporate definite statements to this effect within refined guidelines.

(2) Conflicting evidence from different pieces of data. Mislabeled fields for which this was a factor appeared very similar to another crop in certain features. There were some observable differences, however, in other features. The labeling error seemed to stem from the situation that the analyst did not know which features to weight as more important. These cases point to a need to try to identify which features or data products are most reliable in certain situations and to incorporate this information into refined labeling guidelines. To do this, however, much more data needs to be sampled in the generation of labeling guidelines so that an adequate sample and thus characterization of variation can be made.

(3) Field definition problems. Poorly defined field boundaries, especially in small and/or irregularly shaped field areas created problems related to locating pixels on the reference acquisition and thus in tracking the fields through all available acquisitions. There were difficulties in trying to determine whether one was dealing with a single field or with several fields. Small fields occasionally looked like mixtures between adjacent fields or were not detectable at all because of insufficient spatial resolution. The labeling errors that fell in this category were directly related to data quality and therefore could not be minimized through improvements in labeling guidelines. Field definition problems probably contributed indirectly to analyst errors 5 through 8 by inducing uncertainty, fatigue, and frustration.

(4) The numeric spectral data needed for field identification was not readily available. Although the AI was provided with three-by-three numeric block dumps of three spectral vegetation parameters, these data did not always provide the spectral values near the field center. This was particularly true for sample pixels that fell on field boundaries where the misregistration between a given acquisition and the analyst's reference date was more than one pixel. Although the analysts were free to use the UCB interactive system to gain additional data, they did not always choose this option due to time and scheduling constraints at the time they most desired to use the system. Lack of pure field center spectral data may have been a potential problem for other fields that were not mislabeled; however, other data products, particularly the image products, were apparently sufficient for correct identification in these cases.

(5) Data misregistration. Spectral aids (especially temporal plots) generated for the 209 sample pixels occasionally provided misleading information for pixels near field edges because misregistration threw these pixels into different fields on different acquisitions. The analysts had been instructed to label the sample pixels on a single reference date and to adjust for mis-

registration by means of the numeric block dumps. However, some AI's (particularly those who relied heavily on the temporal plots) either did not make the adjustments correctly, did not understand the concept of labeling on a reference date, or were negligent in checking the data to make the necessary adjustment. Therefore, these AI's frequently labeled a pixel on the basis of a temporal-spectral pattern that was actually a composite of data from two or more fields. A labeling decision might have been correct for the pixel they actually labeled; however, it was not correct for the pixel they were supposed to have labeled. Although misregistration is a data related problem, the errors described here were considered analyst errors because the experienced AI should have been able to make the necessary adjustments for the misregistered fields.

(6) Lack of spectral aid labeling guidelines experience. The mislabeled summer crop errors in this category were attributed to analyst inexperience with the guidelines, spectral aid data products, or subtle aspects of the analysis process, with which a more experienced AI would be more familiar. Although a training session was held in an attempt to overcome the disparity in experience among analysts, some AI's apparently required more intensive instruction than had originally been anticipated or was possible in the limited time available. Many of the errors in this category could have been eliminated had the AI's been provided with longer instruction regarding the use of guidelines, data products, and analysis procedures. In addition, a larger number than two training segments would have been helpful.

(7) Bad calls. Some incorrect labels, when evaluated relative to the data available for analysis, were obviously bad calls probably due to periodic lapses in analyst perception or judgement. Even the most experienced AI could be guilty of this sort of error. A common contributor to bad calls was fatigue, which caused analysts to make hasty decisions without thorough examination of all available pertinent data. Analyst bookkeeping errors were also included in this category.

(8) Miscellaneous ambiguous errors. This final category incorporated analyst errors for which the reasons were not totally clear. These incorrect labels were bad calls in that available data appeared to be sufficient for correct identification. However, these errors were different from those described in category 7 in that certain data characteristics may have contributed to confusion on the part of the analyst. The summer crop labeling errors that were included in this category were not considered to be the direct result of analyst inexperience as described under error factor 6.

To summarize: errors in categories 1 and 2 were of primary concern to this subtask in that they identify actual problem areas for which further research into crop spectral separability and labeling guidelines is required. The remaining error categories were not directly related to the objectives of this subtask, although they do identify other areas in which further work is needed in order to improve labeling accuracy. Categories 3 and 4 involve data problems that were beyond the control of the AI, while the remaining four categories reflect the need for improvement in analysis procedures and analyst training and experience.

Following determination of the error factors that were operative among the twelve analyst/segment pairs under consideration, each incorrect summer crop label was classified according to the error factor category or categories that appeared to be most relevant in accounting for that particular label. For the purpose of this tabulation, each incorrect label was counted as one unit, regardless of whether it represented an entire pixel or merely one-half or one-third of a mixed pixel. If more than one error factor appeared to have contributed to a given incorrect label, each category was counted as a fractional unit. Table 2.15 summarizes the results of the error factor classification as a function of the major summer crop confusions within six frequency of misclassification categories. These categories represent the number of AI's assigning an incorrect label out of the total number of AI's who actually labeled a particular field (see page 2-16 for further discussion of this distinction). For easier interpretation, a tally of the errors in each of these six categories may be found in Table 2.16 as a function of the eight error factor classes. Similarly, Table 2.17 presents error factor class versus crop confusion for all incorrect summer crop labels in the twelve analyst/segment pairs reviewed, for a total of 194 summer crop errors.

The results of the error evaluation indicated that nearly half (47%) of all incorrect labels could be attributed to analyst-related problems (error factors 5 through 8). These analyst problems accounted for nearly all of the errors made in the frequency of misclassification category one of three (Table 2.16) and approximately one-quarter of the errors made by a majority of the AI's (two of two, two of three, and three of three frequency of misclassification categories). Two-thirds of the errors in the remaining frequency of misclassification categories (one of one, one of two) were also attributable to analyst error rather than inadequate guidelines or data.

Thirty-nine (39) per cent of the incorrect labels were directly attributable to problems in the guidelines or in spectral separability (classes 1 and 2). These error factors were the most significant causes of incorrect labels as evidenced by the frequency

of misclassification categories with which they were associated (two of three and three of three). Error factors 1 and 2 were of only minor importance in explaining errors made by a single analyst.

Relative to the seemingly high proportion of summer crop errors attributed to analyst-related problems, certain observations were made regarding analyst performance in the test.

(1) Although analyses of variance revealed no significant differences among analysts, some analysts made a large number of specific kinds of analyst-related errors that other analysts did not. This determination was made by comparing results among AI's for individual segments rather than on overall figures from the twelve analyst/segment pairs. The analysis showed that certain analysts consistently made more errors of a specific type within a given segment than did the other AI's who labeled that segment. This was particularly true of errors related to misregistration (error factor 5). This error factor was particularly prevalent among analysts who relied heavily on temporal plots. Error factor 6, analyst inexperience, was pertinent among the analysts who were less familiar with LACIE-like spectral aid products and analysis procedures associated with the use of quantitative data products. This problem was especially important in regard to separating summer crops from other crop/land use groups. Analysts C and G, who followed an analysis procedure philosophically similar to that described in Subtask C, were not guilty of many analyst-related errors with an exception of some incorrect labels that were related to Analyst G's lack of exposure to satellite data analysis prior to this test.

(2) Certain analysts showed a greater tendency to confuse certain crop types than did other AI's. Analysts B and F committed several corn fields with soybeans--mostly fields that were identified correctly as corn by other analysts. These two analysts were responsible for nearly two-thirds of the overall commission of corn with soybeans that is summarized in Table 2.9. B and F also had the most difficulty in dealing with misregistration, which accounted for most of the above confusion.

(3) In spite of individual analyst problems, the overall analyst accuracy in labeling corn and soybeans was reasonably high. More experience with data analysis in the Corn Belt and more intensive training in the use of labeling guidelines and spectral aid products would have eliminated many of the analyst-related errors.

Based on Central Corn Belt test results and the foregoing evaluation of summer crop labeling errors, the following conclusions were drawn regarding the significance of specific crop confusions:

(1) Corn/soybeans*: Over half of this confusion was due to inadequate temporal-spectral separability relative to currently exploited features (Table 2.17). Error classes 1 and 2 accounted for nearly all of this confusion in segment 854, where several soybean fields did not exceed the maximum GRABS and green canopy TC1 values observed for corn (see Figure 2.2). Closer examination of the incorrectly labeled fields is indicated to determine whether other criteria or features could have been used to identify these fields correctly.

(2) Soybeans/corn: Two-thirds of this confusion was attributed to analyst-related problems. Only about fifteen percent of the error was related to inadequate guidelines or temporal-spectral separability. As previously noted, two analysts were responsible for the majority of this confusion. In only one instance was a corn field mislabeled as soybeans by all three AI's labeling that field. Although further study is indicated regarding temporal-spectral separability between these two crop types, the results indicate the need for procedures or techniques to minimize individual analyst-related performance errors.

(3) Corn/APR (alfalfa, pasture and range): This confusion was almost entirely based on inadequacy of guidelines and spectral separability. This was particularly apparent in segment 883, where incorrect labels were often consistent across all three analysts labeling a field. Guidelines for separating summer crops from APR, other than simple temporal criteria, have not been clearly defined as yet. The temporal-spectral similarity of the mislabeled APR to corn was so great that the AI had no clue that these fields were not corn (see Figures 2.3 and 2.4). Provided the ground data labels are accurate, correct identification in similar situations will have to depend on the development of other labeling criteria or features.

(4) APR/corn: Analyst-related performance error was the primary contributor to this confusion. Although guidelines were not well developed for this confusion situation, simple temporal criteria should have been sufficient to label these fields correctly. Greater AI familiarity with the situation in the Corn Belt may have lessened this type of confusion.

* Incorrect AI label/ground truth label.

(5) SY/APR: Errors involving this confusion were few in number and were explained by the same factors that governed the preceeding category.

(6) APR/SY: Half of this confusion was again due to analyst-related problems. However, 42% of this confusion was a result of inadequate spectral separation in the data based on currently exploited features. The latter factor was particularly important in segment 883. The soybean fields in question were so unlike any other soybean fields previously observed that it was difficult to believe the ground data (see Figure 2.4). Further work is indicated to determine whether the ground data labels are accurate or whether these fields are unique in their temporal-spectral patterns.

(7) C/SR: Although guideline and field definition problems were listed as the two factors contributing to this confusion, an additional factor was the low proportion of sorghum within the segments. This crop type confusion was therefore fairly unimportant in the five Central Corn Belt segments. Criteria for separating unirrigated corn and sorghum are not as yet available to the analysts, particularly in reference to Corn Belt conditions.

(8) Other confusions: Confusions between corn or soybeans and crop/land use groups other than APR were mostly due to poor field definiion or poor analyst judgement. Healthy volunteer vegetation that occupies idle fields in humid environments, however, was observed to be a potential source of moderate crop type confusion.

The Corn Belt Periphery

Results for the five Corn Belt periphery segments are shown in Tables 2.18 through 2.24. Average summer crop labeling accuracies among the periphery segments were moderately to substantially lower than those among the five central Corn Belt segments, although certain individual analyst accuracies were comparable to Central Corn Belt segment accuracies. Combined results from just the three Nebraska segments are presented in Table 2.19. Due to differences in crop types and crop proportions, combined results from the other two periphery segments, 185 and 241, are presented separately in Table 2.20. Average labeling accuracies for combined summer crops (corn,

soybeans, and sorghum) were 73.22% across the three Nebraska segments and 72.35% for combined summer crops (corn, soybeans, sunflowers, sugar beets, and sorghum) across the other two segments. Commission errors (B) were 28.37% and 28.82% for the three Nebraska segments and the remaining two segments, respectively. Average labeling accuracies for corn alone were 77.77% (14.11% commission) in Nebraska and 88.34% (28.63% commission) for segments 185 and 241. Individual segment accuracies for corn (Appendix B) ranged from 19.3% correct in segment 1591 to 97.91% correct in segment 241. Average soybean labeling accuracy for segments 185 and 241 was 47.42% correct (43.39% commission), ranging from 0 to 88.67% correct. Soybeans were not a major crop (i.e. they occupied less than five per cent of the area) in the Nebraska segments. Labeling per cent corrects and commission errors for summer crops other than corn or soybeans may be found in the tables. Aside from sunflowers in segment 185, none of the other summer crops occupied more than five per cent of the area in a segment.

Looking at the types of confusions that accounted for most of the labeling error, it can be seen that 30.96% of the total error (16.83%) within the five periphery segments involved confusion among specific summer crop types (see Table 2.22). This is almost equal to the proportion of total error due to this type of confusion observed in the five Central Corn Belt segments. The error due to this confusion was slightly less (23.03%) for just the three Nebraska segments (1075, 1572, and 1591) shown in Table 2.19.

Confusion between summer crops and the other four crop/land use groups accounted for 21.39% of the total error across the five periphery segments. The proportion of the total error due to this type of confusion, however, varied considerably from segment to segment ranging from 6% of the error in segment 185 to over 50% of the total error in segment 1075.

The remaining 47.65% of the total error involved confusions among land use groups not including the summer crop land use group. This last error proportion was much larger for the five periphery segments than the comparable error figure for the Central Corn Belt segments. This was probably due to the larger proportion of acreages within the periphery segments occupied by non-summer crop land use groups.

As in the Central Corn Belt, the major outside source of confusion with the summer crop group was alfalfa/pasture/range (APR). 15.03% of the total error involved confusion between the summer crop land use group (SC) and the APR land use group. In general most of

the commission of APR to the summer crop group involved calling APR corn (1.19% of the total error). Somewhat less corn was committed to the APR land use group (.78% of the total error). Some sorghum was also committed to APR (.32% of the total error).

Within the summer crop land use group, the major sources of labeling error involved confusions between: 1.) corn and sorghum (35.99% of within-summer crop error--see Table 2.24), 2.) corn and soybeans (29.35% of within-summer crop error), 3.) corn and sunflowers (16.75% of within-summer crop error), and 4.) soybeans and sunflowers (10.98% of within-summer crop error). The remaining within-summer crop confusions were minor confusions: 1.) soybeans and sorghum (2.60% of within-summer crop error), 2.) soybeans and sugar beets (2.31% of within-summer crop error), and 3.) sunflowers and sugar beets (2.02% of within-summer crop error). These lower proportions of the error for confusions between soybeans, sorghum, sunflower and sugar beets are due to lower proportions of these crops within the periphery segments. These confusions would probably be significant in areas where these crops occurred together in larger proportions.

Looking at the three Nebraska segments separately (Table 2.19), 80% of the within-summer crop error involved confusion between corn and sorghum, primarily the commission of corn to sorghum. The majority of the corn-sorghum as well as all soybean-sugar beet errors occurred in segment 1591. Poor temporal-spectral separability and incorrect AI assumptions regarding relative crop proportions were the primary factors behind these errors.

Confusions among summer crops in segments 185 and 241 (Table 2.20) were more diverse than in the Nebraska segments. Approximately 40% of the within-summer crop error involved confusion between corn and soybeans. Nearly twice as many soybean fields were labeled corn, as compared to corn labeled soybeans. This was consistent with the trend observed among the central Corn Belt segments. Another 29% of the within-summer crop error was due to confusion between corn and sunflowers. This was primarily in segment 185, where many sunflower fields did not attain as high a GRABS amplitude as had been predicted in the guidelines. Some confusion between soybeans and sunflowers was also observed in segment 185. This confusion was largely attributable to a single analyst, however. The remaining within-summer crop error involved sorghum in segment 241 and sugar beets in segment 185. Both of these crop types occupied very small proportions of the respective segment areas.

The agricultural environments were much more complex in the periphery segments than in the Central Corn Belt, and thus it was a more difficult labeling task for the analysts. Due to the higher level of complexity of the periphery segments, it was not possible to determine easily and completely the error factors associated with each incorrectly labeled pixel as had been done for the Central Corn Belt segments.

However, summer crop errors were evaluated against the available data to determine which error factors seemed to contribute most significantly to the incorrect labels. The error factors identified for the Central Corn Belt segments were found to be operative in the periphery segments as well. Furthermore, two additional error factors were identified that had not been important in the Central Corn Belt labeling situation. These error factors were a function of lower crop acreage proportions for certain summer crops within the periphery segments. These factors will be discussed in more detail below along with the effect of the previously identified error factors.

Inadequate guidelines and/or data separability appeared to have been significant factors contributing to confusion between the following crops:

(1) Corn versus sorghum. Due to the limited data available for guideline development last year, no consistent temporal-spectral patterns could be identified to separate corn from sorghum, especially when both crops were similarly irrigated or unirrigated within the same area. The only temporal and spectral differences that were observed between the two crops within the guideline development data set were differences between irrigated corn and unirrigated sorghum. The test analysts were, therefore, to rely on cropping practices and relative crop proportion information (contained in county historical statistics) in order to label fields in the test segments. This information was sufficient for segments 1075 and 1572 because the county-level statistics accurately reflected actual segment conditions. However, for segment 1591, county statistics indicated that there should be more sorghum than corn. This in fact was not true for the segment. Since the AIs did not have adequate spectral guidelines enabling them to verify their expectations relative to these crops at the segment level, a significant degree of confusion resulted. More corn fields were incorrectly labeled as sorghum than vice versa because the analysts judged that questionable fields were more probably sorghum based on the county proportions data.

(2) Corn versus soybeans. Some spectral confusion was observed between these crops, particularly in segment 241, where the upper limits of the corn distribution and the lower limits of the soybean distribution in GRABS versus TC1 space overlapped (see Figure 2.5). Mislabeling of corn fields as soybeans in these segments appeared to be more directly related to data separation problems than had been the case in the Central Corn Belt.

(3) Corn versus sunflowers. Confusion occurred in segments 185 and 241 between corn fields and "low greenness" sunflower fields. Some sunflowers did not attain expected maximum GRABS values. Separation on the basis of relative brightness appeared to be possible in many cases (see Figure 2.6), but the analysts had not been informed to expect "non-green" sunflowers by the labeling guidelines.

(4) Soybeans versus sorghum. Guidelines for separating these two crops were not developed last year due to unavailability data.

(5) Unirrigated corn and sorghum versus alfalfa/pasture/range. Infrared reflectance from a few unirrigated corn and soybean fields was so low that these fields were not recognizable as summer crops based on current temporal-spectral criteria.

Further work is indicated in these areas of crop confusion to (1) clarify crop separability according to current temporal-spectral criteria and (2) determine other characteristics that may be used to separate crops when current criteria are not sufficient.

Problems arising from analyst inexperience contributed to many incorrect labels, particularly those involving confusion between a summer crop and a non-summer crop. Analysts who were less familiar with the Great Plains environment occasionally misinterpreted temporal patterns that should have been sufficient to separate summer crops from other groups (for example, analyst F in segment 1075, analysts F and G in segment 241). Lack of experience in applying guidelines to the spectral aid data products put some AIs at a disadvantage when trying to identify as many as four summer crop distributions in a segment. When summer crop errors were examined for consistency across analysts, it was found that the less experienced AIs made more "one of three" and "one of four" errors relative to other analysts interpreting the same segment. Had more time been available for training and familiarization before the test, many of these errors probably would not have been made.

Two additional error factors relating to small summer crop proportions were identified. These error factors did not appear to be significant in the Central Corn Belt, where corn and soybeans occupied major proportions within the segments and other confusion crops were rarely found.

(1) Minor summer crops were often overlooked by analysts, who assumed that these crops were "not important" within a given segment. Sugar beets in segment 185, sunflowers in segment 241, soybeans in segments 241 and 1591, and sorghum in segments 241, 1075 and 1572 were largely overlooked because historical county agricltural statistics indicated that these crops occupied less than five percent of the area of the counties in which the segments were located. Although the presence of a minor crop was occasionally detected and identified by an AI from segment-level temporal-spectral data (for example, analyst D found the sugar beet fields in segment 185), even fields that had a "classical" crop pattern according to the temporal-spectral guidelines were mislabeled. Minor crops within a segment tended to be committed to the more predominant summer crops such as corn.

(2) The within segment sampling rate for scatter plots was not always sufficient for an analyst to detect and identify summer crops with small segment proportions, even if spectral separability existed in the data. This inadequate sampling rate contributed to the problem of overlooking minor crops cited above. This factor also affected labeling accuracies for the more dominant summer crops within the periphery segments, since even those proportions were not as high as corn and soybean proportions in the Central Corn Belt. The ten-by-ten pixel sampling rate (209 dots) used to generate GRABS versus TC1 scatterplots did not draw enough samples to ensure the detection of minor crop distributions by the AI. The analyst could not tell whether a few isolated samples represented a separate summer crop or were just extreme representatives of the dominant summer crop distributions. This situation was most apparent in 185, a segment with fairly clean separation in the spectral data between the four summer crops. Analyst D made the majority of the within-summer crop errors in this segment, using scatter plots generated from the ten-by-ten pixel sample. The other two analysts, A and C, used scatter plots generated by a five-by-five pixel sample that enabled them to detect and identify distributions

for three of the four summer crops present. Examples of scatter plots generated by both sampling rates are included in Figures 2.7 and 2.8 for comparison.

Inconvenient accessibility to pure numeric spectral data from field centers compounded the problems arising from small summer crop proportions. Summer crop appearances on the PFC products were not sufficient to make up for the absence of pure quantitative spectral values.

2.3.4 CONCLUSIONS AND RECOMMENDATIONS

The following section summarizes the relative temporal-spectral characteristics that were observed for specific summer crops from interpretation test data (qualitative image data, quantitative spectral data, and test results). The observed relationships, in most cases, confirm relationships observed last year in the initial labeling guidelines. However, possibilities for expanding and clarifying the guidelines were noted. In addition, areas were identified for which currently exploited labeling features are not adequate for crop type detection and identification.

Corn versus Soybeans

(1) The vast majority of soybean fields had higher maximum GRABS amplitudes than did corn. This relationship appeared to be consistent over all three geographic regions that were represented in the test (Central Corn Belt, Nebraska and extreme northern U.S. Great Plains). 7/5 VI (2xMSS7/MSS5) amplitudes were not examined.

(2) A small degree of spectral overlap was observed in the respective GRABS ranges of corn and soybeans, probably due to poor canopy development in soybeans and greater water availability to corn.

(3) Both corn and soybeans seemed to "travel up" or occur on the same "green arm" (Figure 2.6). Soybeans usually occupied the higher positions on the green arm, i.e. higher GRABS and Brightness values than corn but on the same green arm projection. Soybean fields that did not attain higher GRABS values than corn overlapped the corn distribution in that there was no difference in brightness between the "lower-greenness" soybean fields and corn fields.

(4) The greatest separability between these two crops occurred after both crops had reached maximum GRABS values (spectral peak) and before soybeans had fallen off significantly from the peak. This optimum separation period appeared to coincide with the early grain filling stages in corn (blister through early dough) and the pod setting and early seed filling stages in soybeans (biostages R3 through R6 on the Fehr-Caviness scale). These biostages occurred during the month of August in all seven Central Corn Belt and far northern U. S. Great Plains test segments.

(5) Temporal delay in the green-up of soybean fields was not consistent across all segments or across all fields within a segment. Differences in observed green-up time between corn and soybeans ranged from substantial in segment 854 to insignificant in segment 185. Since the temporal delay in soybean green-up is a function of the differences in planting time between corn and soybeans which varies with geographic area, weather conditions, and the individual farmer, this separation criterion does not appear to be consistently applicable. However, if the latest time at which corn greens up within a region can be established with reasonable certainty, any observable delay in field green-up beyond that time may be useful in separating "low-greenness" soybeans from corn.

(6) Additional features that show potential value for separating corn from soybeans were suggested from the test data. Further examination is required, however, before any attempt can be made to incorporate these features into the labeling guidelines. These features include relative pixel-to-pixel spectral variation (corn may be less variable than soybeans) and shape of the temporal plots of GRABS values for the two crops. Initial examinations indicate that corn (a crop that utilizes the entire length of the growing season) may have a generally flatter curve with slower rates of green-up and fall-off than soybeans. In addition the corn curve may have a plateau or secondary peak after the maximum spectral peak (Figure 2.9). Soybeans seem to have two basic curve shapes depending on whether they are planted at the normal planting time for full season growth or late-planted (e.g. double-cropped or replanted after a crop failure) for short season growth. The former may have a relatively high peak and a moderate rate of fall-off, whereas the latter may not always reach a high peak but appear to fall off more rapidly (Figure 2.10).

Corn versus Sunflowers

Corn and sunflower comparisons were limited to a single geographic area: the far northern U.S. Great Plains (segments 185 and 241).

(1) A large number of sunflower fields had higher maximum GRABS amplitudes than did corn. 7/5 VI amplitudes were not examined.

(2) However, several sunflower fields did not attain high GRABS values at peak. This was not clearly recognized in the initial labeling guidelines.

(3) Regardless of relative GRABS values, sunflowers had higher TC1 (brightness) values than did corn. Sunflowers appeared to travel up a "green arm" approximately parallel to that traveled by corn and soybeans but displaced to the right (higher brightness) of the corn-soybean "green arm" (Figure 2.6).

(4) The best separation between corn and sunflowers was observed in segment 185 on the 24 July acquisition. Corn was in the tasseling stage and sunflowers were blooming (sunflower biostage approximated from North Dakota statewide crop calendar).

(5) Temporal separation criteria were not examined.

Soybeans versus Sunflowers

Soybean and sunflower comparisons were limited to the far northern U.S. Great Plains (segments 185 and 241).

(1) Soybeans and sunflowers reached approximately the same maximum GRABS amplitudes. Some soybean fields actually had slightly higher GRABS values, but this difference was not consistent enough to use as a criterion for separation. 7/5 VI amplitudes were not examined.

(2) Sunflowers tended to have higher TC1 values for a given GRABS value than did soybeans (Figure 2.6).

(3) The best separation between soybeans and sunflowers was observed in segment 185 on the 12 August acquisition. Sunflowers had bloomed (approximate) and soybeans were in the pod setting stage.

(4) Temporal separation criteria were not examined.

Corn versus Sorghum

Opportunities for comparing corn and sorghum were limited, confined primarily to the three Nebraska segments.

(1) No reliable separation between corn and sorghum was observed based on currently exploited labeling features when both crops were either irrigated or unirrigated.

(2) Both crops reached approximately the same maximum GRABS amplitudes when water availability was equal. 7/5 VI amplitudes were not examined.

(3) The sorghum fields observed for segment 1591 tended to have slightly higher green canopy TC1 values than most corn fields at similar GRABS levels, but the consistency of this tendency is unknown and a few brighter corn fields were also noted (see Figure 2.11).

(4) Sorghum appeared to be slightly later than corn in overall temporal development, but the differences were not sufficient to allow separation based on only this minor difference.

Soybeans versus Sorghum

Comparisons of soybeans and sorghum are based on extremely limited observations due to the infrequent occurrence of both crops in the same segment.

(1) Soybeans reached higher maximum GRABS amplitudes than sorghum. 7/5 VI amplitudes were not examined.

(2) Soybeans had higher TC1 values when GRABS amplitudes were substantially higher than those of sorghum. When GRABS values were closer to the sorghum levels, soybeans did not

appear to be any brighter. The possibility is suggested that sorghum actually has higher TC1 values than soybeans for a given GRABS amplitude, but this could not be confirmed due to insufficient data.

(3) Temporal separation criteria were not examined.

<u>Sugar Beets versus Other Summer Crops</u>

Sugar beets were only found in segment 185.

(1) Sugar beets attained higher maximum GRABS amplitudes than did corn. 7/5 VI amplitudes were not examined but a similar relationship is expected.

(2) Sugar beets reached approximately the same GRABS levels as soybeans and sunflowers and were not separable from the two crops based on this labeling feature alone.

(3) Sugar beets appeared to travel up the same "green arm" as sunflowers (Figure 2.6), parallel to and brighter than the "green arm" traveled by corn and soybeans.

(4) Sugar beets displayed a unique temporal GRABS pattern characterized by high but fluctuating values during the green canopy phase until immediately before harvest when the values sharply drop. Sugar beets do not turn before harvest and go from full green canopy state to clean bare soil upon harvest. Thus, this unique temporal pattern appeared to be the most reliable feature for separating sugar beets from sunflowers or any other summer crop observed.

<u>Summer Crops versus Alfalfa/Pasture/Range (APR)</u>

(1) APR was generally separable from summer crops based on simple temporal criteria. APR green canopy was detectable earlier in the season than summer crops and was often still green after summer crops had matured and been harvested. Periodic cuttings of alfalfa resulted in alternating "green canopy" and "harvest" signatures in a field throughout the growing season ("blinking out").

(2) Some pasture and hay fields were not separable from summer crops based on temporal criteria. These fields did not appear to be separable on the basis of currently exploited spectral features either. There is some question as to the accuracy of the ground data for certain of these fields.

The preceding areas of crop confusion for which guideline modifications have not been specified require further study to (1) define other crop temporal-spectral features that might lead to increased labeling accuracy and (2) determine which features and data products should be weighted most heavily in given labeling situations. The first task addresses the failure of currently defined labeling features to provide adequate separation between certain crops. The second addresses the analyst's need for guidelines to evaluate conflicting pieces of evidence.

In addition to the crop confusion problems addressed above, which are directly related to the characterization of crop temporal-spectral patterns and the development of labeling guidelines for the analyst, improvement in the following data analysis areas were indicated to increase labeling accuracy:

(1) Spectral Aids

The ten-by-ten pixel sample (209 dots) used in the test was clearly inadequate for summer crops that did not occupy a large portion of the segment area. This stresses the need for a data sample that sufficiently represents all major crops of interest and a format for presentation to the AI that optimizes his ability to detect and identify these distributions.

The need for an efficient method of extracting and providing pure quantitative spectral data from field centers to the analyst was also identified. Without pure quantitative spectral data, the AI is unable to make the subtle spectral comparisons that are often necessary to label a field accurately.

(2) Analyst Performance

Many of the incorrectly assigned summer crop labels in the test appeared to be directly attributable to individual

analyst problems. Thorough analyst familiarization with the use of ancillary and spectral (particularly quantitative) data products is called for in order to minimize analyst errors and differences in individual analyst performance.

However, it was obvious that the vast quantities of data that needed to be examined for each pixel created difficulties for even the most experienced analysts, resulting in bad calls related to fatigue and confusion. Guidelines for the efficient analysis of numerous data products are urgently needed. In particular, by incorporating more machine-aided analyst procedures we may be able to reduce substantially the number of bad calls. Time-consuming and fatigue-inducing multiple acquisition comparisons could be relegated to the machine, leaving the analyst free to evaluate the resulting information with a clear head. The consistent application of established decision rules among analysts within a segment would also be facilitated through machine-interactive processing.

Table 2.4 Crop and Confidence Codes Used in Test

LAND USE/CROP CODES

SC	Summer Crops		SSG	Spring Small Grains	
	BN	Dry Beans		B	Barley
	C	Corn		FX	Flax
	CN	Cotton		O	Oats
	PO	Potatoes		SW	Spring Wheat
	RI	Rice	APR	Alfalfa/Pasture/Range	
	SB	Sugar Beets		A	Alfalfa
	SF	Safflower		H	Hay
	SR	Sorghum		P	Pasture/Range
	SU	Sunflowers		G	Grass
	SY	Soybeans			
			I	Idle (Fallow, Stubble, Bare Soil)	
WSG	Winter Small Grains		NA	Non-Agricultural	
	W	Winter Wheat		RD	Road
	R	Winter Rye		T	Trees, Riparian
				WA	Water
				U	Urban

CONFIDENCE CATEGORIES

(1) Absolute confidence in first label assignment; alternate label improbable but a very slight possibility

(2) First label assignment highly probable; alternate label(s) of low to medium probability

(3) First and alternate labels highly probable; first label of slightly higher probability than alternate(s)

(4) First label and alternate(s) equally probable

Table 2.5 Definition of Variables of Interest

(1) $$P = \frac{\text{\# sample pixels in class of interest (from ground data)}}{\text{total \# sample pixels}} \times 100$$

(2) $$\text{AI Error} = \hat{P}-P, \text{ where } \hat{P} = \frac{\text{\# sample pixels assigned by AI to class of interest}}{\text{total \# sample pixels}} \times 100$$

(3) $$\text{RMS} = \sqrt{\frac{\text{sum of squared AI errors}}{\text{\# AI's}}}$$

(4) $$\text{\% Correct} = \frac{\text{\# sample pixels correctly assigned by AI to class of interest}}{\text{total \# sample pixels in class of interest}} \times 100$$

(5) $$\text{\% Commission (A)} = \frac{\text{\# sample pixels incorrectly assigned by AI to class of interest}}{\text{total \# sample pixels} - \text{\# pixels in class of interest}} \times 100$$

$$\text{\% Commission (B)} = \frac{\text{\# sample pixels incorrectly assigned by AI to class of interest}}{\text{total \# sample pixels assigned by AI to class of interest}} \times 100$$

TABLE 2.6 SUMMARY OF INTERPRETATION TEST RESULTS OVER ALL ANALYSTS AND SEGMENTS

Land Use Group or Crop	P(%)	AI Error	RMS[1]	% Correct	% Commission (A)	% Commission (B)
SUMMER CROPS[2]	49.70	- .16	2.58	95.95	3.69	3.74
Corn	29.07	.87	4.53	90.64	5.07	12.00
Soybeans*	18.27	-1.07	3.08	85.68	1.89	8.97
Sunflowers*	1.69	- .29	2.39	68.40	.25	17.71
Sugar Beets*	.11	- .07	.84	26.67	.04	33.33
Sorghum*	.56	.36	3.25	22.08	.81	86.54
Combined[3]	49.70	- .16	2.58	87.14	-	12.58
OTHER	50.30	.16	2.58	96.31	-	3.99
Small Grains*	8.11	- .36	2.23	80.22	1.26	16.08
Alfalfa/Pasture/Range	30.09	2.39	6.14	90.60	7.46	16.06
Idle*	2.43	- .66	2.42	39.02	.85	46.57
Non-Agriculture	9.53	-1.08	3.65	81.28	.77	8.24

* P<5% in some segments.

1 Incorporates only those segments in which category occurred.

2 Crop group level - specific crop labels not considered.

3 Crop type level - specific crop labels used to calculate % correct and % commission.

TABLE 2.7 SUMMARY OF INTERPRETATION TEST RESULTS OVER ANALYST/SEGMENT PAIRS IN SBIB DESIGN[1]

Land Use Group or Crop	P(%)	AI Error	RMS[2]	% Correct	% Commission (A)	% Commission (B)
SUMMER CROPS[3]	53.63	- .52	2.17	96.13	3.36	2.93
Corn	31.93	.04	4.88	90.11	4.70	10.01
Soybeans*	20.77	-1.17	3.34	87.47	1.81	7.31
Sunflowers*	.22	- .20	1.60	11.11	0	0
Sugar Beets*	0	.05	.61	0	.05	100.00
Sorghum*	.72	.75	4.53	28.33	1.27	86.10
Combined[4]	53.63	- .52	2.17	87.94	-	11.20
OTHER	46.37	.52	2.17	96.64	-	4.43
Small Grains*	5.32	- .58	2.09	61.02	1.58	31.56
Alfalfa/Pasture/Range	29.12	3.23	6.86	90.68	8.39	18.37
Idle*	2.73	- .69	2.97	39.53	.99	47.06
Non-Agriculture	7.83	-1.35	3.58	76.28	.56	7.90

* $P<5\%$ in some segments.

1 Excludes first two interpretations by each analyst.

2 Incorporates only those segments in which category occurred.

3 Crop group level - specific crop labels not considered.

4 Crop type level - specific crop labels used to calculate % correct and % commission.

Table 2.8 Results of Analysis of Variance

Variable of Interest *	Significance of Analyst Effect	Significance of Segment Effect	Significance of Scheffé's Test
% Correct - Corn	ns **	.001	.001
% Correct - Summer Crops ***	ns	.001	.001
Commission A - Corn	ns	ns	
Commission B - Corn	ns	ns	
Commission B - Summer Crops ***	ns	.001	.001
AI Proportion Estimate Error - Corn	ns	.025	.05

* Definitions for the above variables are presented in Table 2.5.

** "ns" means "not significant at the .05 level of significance".

*** Variables designated "summer crops" above measure performance in the assignment of summer crops pixels to the proper summer crop type; they do not assess the analysts' ability to assign pixels to the more general category "Summer Crops."

TABLE 2.9 COMBINED INTERPRETATION TEST RESULTS FOR CORN BELT SEGMENTS 145, 824, 854, 883, AND 886

GROUND DATA

ANALYST	C	SY	SR	SG	APR	Other Ag.	NA	Total	% Commission (B)
C	1337.50	78.33	3.00	2.00	35.00	3.00	2.83	1461.67	8.50
SY	45.33	1028.17			15.00	1.50		1090.00	5.67
SR			0					0	0
SG		1.50		8.00	24.00	3.33	.50	37.33	78.57
APR	32.50	39.83		25.50	378.50	9.50	31.50	517.33	26.84
Other Ag.	1.50	3.00		4.50	5.00	4.50	15.50	34.00	88.24
NA	3.00	4.00	1.00	1.50	13.83	7.50	356.83	387.67	7.95
Total	1419.83	1154.83	4.00	41.50	471.33	29.33	407.17	3528.00	11.75
% Correct	94.20	89.03	0	19.28	80.30	15.34	87.63	88.25	
Proportion %	40.24	32.73	.11	1.18	13.35	.83	11.54		

C - Corn
SY - Soybeans
SR - Sorghum
SG - Small Grains
APR - Alfalfa/Pasture/Range
Other Ag. - Other Agriculture
NA - Non Agriculture

TABLE 2.10 DISTRIBUTION OF LABELING ERROR AS A % OF TOTAL # OF LABELED PIXELS IN CENTRAL CORN BELT SEGMENTS 145, 824, 354, 883 AND 886

GROUND DATA

ANALYST	SC	SG	APR	Other Ag.	NA	Total
SC	3.59**	.06	1.42	.13	.08	5.28
SG	.04	---	.68	.09	.01	.82
APR	2.05	.72	----	.27	.89	3.93
Other Ag.	.13	.13	.14	---	.44	.84
NA	.23	.04	.39	.22	---	.88
Total	6.04	.95	2.63	.71	1.42	11.75*

SC - Summer Crops
SG - Small Grains
APR - Alfalfa/Pasture/Range
Other Ag. - Other Agriculture Including Idle
NA - Non Agriculture

* 414.5 pixels (11.75% of all labeled pixels) were incorrectly labeled.
** 126.67 pixels (3.59% of all labeled pixels) were incorrectly labeled as to specific summer crop type but were correctly assigned to the summer crop land use group.

TABLE 2.11 DISTRIBUTION OF LABELING ERROR BETWEEN OR WITHIN CROP GROUPS AS A % OF TOTAL # OF INCORRECTLY LABELED PIXELS IN CENTRAL CORN BELT SEGMENTS 145, 824, 854, 883 & 886

	SC	SG	APR	Other Ag.	NA	
SC	30.55	.85	29.52	2.22	2.64	
SG			11.90	1.88	.43	
APR				3.49	10.90	
Other Ag.					5.61	
						100.00*

SC - Summer Crops
SG - Small Grains
APR - Alfalfa/Pasture/Range
Other Ag. - Other Agriculture Including Idle
NA - Non Agriculture

* 100 % of 414.5 incorrectly labeled pixels (11.75% of all labeled pixels).

TABLE 2.12 DISTRIBUTION OF LABELING ERROR WITHIN SUMMER CROP LAND USE GROUP AS A % OF TOTAL # OF LABELED PIXELS IN CENTRAL CORN BELT SEGMENTS 145, 824, 854, 883 AND 886

		GROUND DATA			
		C	SY	SR	Total
ANALYST	C	----	2.22	.09	2.31
	SY	1.28	----	0	1.28
	SR	0	0	----	0
	Total	1.28	2.22	.09	3.59*

C - Corn
SY - Soybeans
SR - Sorghum

* 126.67 pixels (3.59% of all labeled pixels) were incorrectly labeled as to specific summer crop type but were correctly assigned to the summer crop land use group.

TABLE 2.13 DISTRIBUTION OF LABELING ERROR WITHIN SUMMER CROP LAND USE GROUP AS A % OF TOTAL # OF PIXELS CORRECTLY IDENTIFIED AS SUMMER CROPS BUT INCORRECTLY LABELED AS TO SPECIFIC CROP TYPE - CENTRAL CORN BELT SEGMENTS 145, 324, 854, 883 & 886

GROUND DATA

ANALYST		C	SY	SR	
	C	----	61.84	2.51	
	SY	35.65	---	0	
	SR	0	0	----	
					100.00*

C - Corn

SY - Soybeans

SR - Sorghum

* 100% of 126.67 incorrectly labeled pixels (3.59% of all labeled pixels).

TABLE 2.15 SUMMARY OF SUMMER CROP LABELING ERRORS IN CENTRAL CORN BELT SEGMENTS 824, 854, 883 AND 886***

1 of 1* CROP CONFUSION**

ERROR CLASS	C/SY	SY/C	C/APR	APR/C	SY/APR	APR/SY	Total
1	1.0		3.0				4.0
2							
3		.5		1.0		.5	2.0
4	.5						.5
5	.5	.5		1.0		1.5	3.5
6						1.0	1.0
7				1.0	1.0	1.0	3.0
8							
Total	2.0	1.0	3.0	3.0	1.0	4.0	14.0

2 of 2* CROP CONFUSION**

ERROR CLASS	C/SY	SY/C	C/APR	APR/C	SY/APR	APR/SY	Total
1	1.0		2.0			2.0	5.0
2							
3		1.0	2.0	1.0			4.0
4	1.0						1.0
5							
6							
7							
8						2.0	2.0
Total	2.0	1.0	4.0	1.0		4.0	12.0

1 of 2* CROP CONFUSION**

ERROR CLASS	C/SY	SY/C	C/APR	APR/C	SY/APR	APR/SY	Total
1							
2							
3		.5	.5				1.0
4	.5	.5					1.0
5	4.5	1.0	.5				6.0
6							
7	1.0	1.0					2.0
8	1.0		1.0				2.0
Total	7.0	3.0	2.0				12.0

2 of 3* CROP CONFUSION**

ERROR CLASS	C/SY	SY/C	C/APR	APR/C	SY/APR	APR/SY	Total
1	5.0	2.0	1.0	.5	1.0	3.0	12.5
2	10.0		.5				10.5
3	2.0	2.0					4.0
4	2.0		.5				2.5
5	2.0	7.0			2.0	2.0	13.0
6				2.5	2.0		4.5
7					1.0		1.0
8							
Total	21.0	11.0	2.0	3.0	6.0	5.0	48.0

1 of 3* CROP CONFUSION**

ERROR CLASS	C/SY	SY/C	C/APR	APR/C	SY/APR	APR/SY	Total
1		1.5		.5			2.0
2	2.0						2.0
3	1.0			.5			1.5
4							
5	3.0	2.0		2.0		3.0	10.0
6	1.0	2.5		4.5		1.0	9.0
7	1.0	5.0		3.0	1.0	1.0	11.0
8	3.0	[illegible]		2.5			6.5
Total	12.0	14.0		13.0	[illegible]	5.0	44.0

3 of 3* CROP CONFUSION**

ERROR CLASS	C/SY	SY/C	C/APR	APR/C	SY/APR	APR/SY	Total
1	7.0	1.5	14.0		.5	6.0	29.0
2	7.0						7.0
3	2.0	1.5		1.5		1.0	6.0
4							
5				1.5	.5		2.0
6							
7							
8						1.0	1.0
Total	16.0	3.0	14.0	3.0	1.0	8.0	45.0

* # of AIs assigning incorrect label/#AI's labeling field.

** Incorrect AI label/ground data label. See Table 2.4 for definition of crop codes.

*** Excludes first or second interpretation by an analyst.

TABLE 2.16 ERROR FACTOR CLASSES VERSUS FREQUENCY OF MISCLASSIFICATION - CENTRAL CORN BELT SEGMENTS 324, 354, 883 AND 386*

OF AI'S ASSIGNING INCORRECT LABEL/# AI'S LABELING FIELD

ERROR FACTOR CLASS	1/1	1/2	1/3	2/2	2/3	3/3	Total
1	4.0	0	2.0	5.0	15.5	30.0	56.5
2	0	0	2.0	0	10.5	7.0	19.5
3	4.0	1.0	1.5	4.0	4.0	7.0	21.5
4	.5	1.0	0	1.0	2.5	0	5.0
5	4.5	6.0	11.0	0	13.0	2.0	36.5
6	1.0	0	9.0	0	5.5	0	15.5
7	3.0	3.0	12.0	0	1.0	1.0	20.0
8	0	3.0	11.5	2.0	1.0	2.0	19.5
Total	17.0	14.0	49.0	12.0	53.0	49.0	194.0

* Excludes first or second interpretation by an analyst.

TABLE 2.17 FREQUENCY OF CROP CONFUSIONS BY ERROR FACTOR CLASS - CENTRAL CORN BELT SEGMENTS 824, 854, 883 AND 886*

ERROR FACTOR CLASS

CROP CONFUSION

AI/GD**	1	2	3	4	5	6	7	8	Total
C/SY	14.0	19.0	5.0	4.0	10.0	1.0	2.0	4.0	59.0
SY/C	5.0	0	5.5	.5	10.5	2.5	6.0	3.0	33.0
C/APR	20.0	.5	2.5	.5	.5	0	0	1.0	25.0
APR/C	1.0	0	4.0	0	4.5	7.0	4.0	2.5	23.0
SY/APR	1.5	0	0	0	2.5	2.0	3.0	0	9.0
APR/SY	11.0	0	1.5	0	6.5	2.0	2.0	3.0	26.0
C/SR	1.0	0	1.0	0	0	0	0	0	2.0
C/SG	0	0	0	0	1.0	0	1.0	0	2.0
C/I	0	0	0	0	0	0	1.0	0	1.0
I/C	0	0	1.0	0	1.0	0	0	0	2.0
SG/SY	1.0	0	0	0	0	0	0	1.0	2.0
I/SY	2.0	0	1.0	0	0	0	0	0	3.0
NA/SY	0	0	0	0	0	1.0	1.0	3.0	5.0
NA/SR	0	0	0	0	0	0	0	1.0	1.0
C/NA	0	0	0	0	0	0	0	1.0	1.0
TOTAL	56.5	19.5	21.5	5.0	36.5	15.5	20.0	19.5	194.0

C - Corn
SY - Soybeans
SR - Sorghum
APR - Alfalfa/Pasture/Range
I - Idle
SG - Small Grains
NA - Non Agriculture

* Excludes first or second interpretation by an analyst.

** Incorrect AI label/ground data label. See Table 2.4 for definition of crop codes.

TABLE 2.18 COMBINED INTERPRETATION TEST RESULTS FOR CORN BELT PERIPHERY SEGMENTS 185, 241, 1075, 1572, AND 1591

GROUND TRUTH

ANALYST	C	SY	SU	SB	SR	SG	APR	Other Ag.	NA	Total	% Commission (B)
C	466.50	29.0	27.5		11.50	5.0	39.33	5.0	4.5	588.33	20.71
SY	21.83	43.83	6.0	3.0	3.5	4.5	2.0	3.0		87.67	50.00
SU	1.5	13.00	79.0	2.5						96.0	17.71
SB		1.0	1.0	2.0			1.0			5.0	60.00
SR	50.83	1.0			8.5		1.0	.5	1.33	63.17	86.54
SG	2.5	1.0				437.33	36.0	13.5	3.0	493.33	11.35
APR	25.83	2.5	1.5		10.5	60.5	1488.17	58.5	59.0	1706.5	12.79
Other Ag.	1.0	3.0			.5	5.5	12.5	61.33	4.0	87.83	30.34
NA	.5	2.0	.5			.33	9.0	4.5	173.83	190.67	8.83
Total	570.5	96.33	115.5	7.5	34.5	513.67	1589.0	146.33	245.67	3319.0	16.83
% Correct	81.77	45.50	68.40	26.67	24.64	85.14	93.65	41.91	70.76	83.17	
Proportion(%)	17.19	2.9	3.48	.23	1.04	15.48	47.88	4.41	7.40		

C - Corn
SY - Soybeans
SU - Sunflowers
SB - Sugar Beets
SR - Sorghum

SG - Small Grains
APR - Alfalfa/Pasture/Range
Other Ag. - Other Agriculture, Including Idle
NA - Non Agriculture

TABLE 2.19 COMBINED INTERPRETATION TEST RESULTS FOR CORN BELT PERIPHERY SEGMENTS 1075, 1572 AND 1591 (NEBRASKA)

GROUND DATA

ANALYST	C	SY	SB	SR	SG	APR	I	Other Ag.	NA	Total	% Commission (B)
C	275.83	2.0		7.0		29.33	4.0		3.0	321.17	14.11
SY	7.5	1.0		2.5			1.0			12.0	91.67
SB		1.0	0			1.0				2.0	100.00
SR	50.83	1.0		8.5		1.0	.5		1.33	63.17	86.54
SG					17.83	13.0	6.0		1.0	37.83	52.87
APR	20.0	1.0		10.5	23.50	1240.34	38.50		58.0	1391.84	10.88
I				.5	4.0	9.0	50.33		2.5	66.33	24.12
Other Ag.					.5			0		.5	100.00
NA	.5				.33	6.0	4.0		75.33	86.17	12.57
Total	354.67	6.0	0	29.0	46.17	1299.67	104.33		141.17	1981.0	15.74
% Correct	77.77	16.67	0	29.31	38.62	95.43	48.24		53.36	84.26	
Proportion(%)	17.90	.30	0	1.46	2.33	65.61	5.27		7.13		

C - Corn
SY - Soybeans
SB - Sugar Beets
SR - Sorghum
SG - Small Grains

I - Idle
Other Ag. - Other Agriculture
NA - Non Agriculture

TABLE 2.20 COMBINED INTERPRETATION TEST RESULTS FOR CORN BELT PERIPHERY SEGMENTS 185 AND 241

GROUND DATA

ANALYST	C	SY	SU	SB	SR	SG	APR	I	NA	Other Ag.	Total	% Commission (B)
C	190.67	27.00	27.50		4.5	5.0	10.0	1.0	1.5		267.17	28.63
SY	14.33	42.83	6.0	3.0	1.0	4.5	2.0	2.0			75.67	43.39
SU	1.50	13.00	79.0	2.5							96.0	17.71
SB			1.0	2.0							3.0	33.33
SR					0						0	
SG	2.50	1.0				419.5	23.0	7.5	2.0		455.5	7.90
APR	5.83	1.5	1.5			37.0	247.83	20.0	1.0		314.67	21.24
I	1.0	3.0				1.5	3.5	10.5	1.5		21.0	50.0
NA		2.0	.5				3.0	.5	98.5		104.5	5.74
Other Ag.								.5		0	.5	100.00
Total	215.83	90.33	115.5	7.5	5.5	467.5	289.33	42.0	104.5		1338.0	18.47
% Correct	88.34	47.42	68.40	26.67	0	89.73	85.66	25.0	94.26		81.53	
Proportion(%)	16.13	6.75	8.63	.56	.41	34.94	21.62	3.14	7.81			

C - Corn
SY - Soybeans
SU - Sunflowers
SB - Sugar Beets
SR - Sorghum

SG - Small Grains
APR - Alfalfa/Pasture/Range
I - Idle
Other Ag. - Other Agriculture
NA - Non Agriculture

TABLE 2.21 DISTRIBUTION OF LABELING ERROR AS A % OF TOTAL # OF LABELED PIXELS IN CORN BELT PERIPHERY SEGMENTS 185, 241, 1075, 1572 AND 1591

GROUND DATA

ANALYST	SC	SG	APR	Other Ag.	NA	Total
SC	5.21**	.29	1.31	.26	.18	7.25
SG	.11	--	1.08	.41	.09	1.69
APR	1.22	1.81	--	1.76	1.77	6.56
Other Ag.	.14	.18	.38	--	.12	.82
NA	.09	.01	.27	.14	--	.51
Total	6.77	2.29	3.04	2.57	2.16	16.83*

SC = Summer Crops
SG = Small Grains
APR = Alfalfa/Pasture/Range
Other Ag. = Other Agricultural Including Idle
NA = Non-Agriculture

* 558.59 pixels (16.83% of all labeled pixels) were incorrectly labeled.
** 173.08 pixels (5.21% of all labeled pixels) were incorrectly labeled as to specific summer crop type but were correctly assigned to the summer crop land use group.

TABLE 2.22 DISTRIBUTION OF LABELING ERROR BETWEEN OR WITHIN CROP GROUPS AS A % OF TOTAL # OF INCORRECTLY LABELED PIXELS IN CORN BELT PERIPHERY SEGMENTS 185, 241, 1075, 1572 AND 1591

	SC	SG	APR	Other Ag.	NA	
SC	30.96	2.38	15.03	2.38	1.60	
SG			17.17	3.51	.59	
APR				12.72	12.12	
Other Ag.					1.54	
						100.00*

SC = Summer Crop
SG = Small Grain
APR = Alfalfa/Pasture/Range
Other Ag. = Other Agriculture Including Idle
NA = Non Agriculture

* 100% of 558.59 incorrectly labeled pixels (16.83% of all labeled pixels).

TABLE 2.23 DISTRIBUTION OF LABELING ERROR WITHIN SUMMER CROP LAND USE GROUP AS A % OF TOTAL # OF LABELED PIXELS IN CORN BELT PERIPHERY SEGMENTS 185, 241, 1075, 1572 AND 1591

GROUND DATA

ANALYST	C	SY	SU	SB	SR	Total
C	--	.86	.83	0	.35	2.04
SY	.66	--	.18	.09	.11	1.04
SU	.05	.39	--	.08	0	.52
SB	0	.03	.03	--	0	.06
SR	1.52	.03	0	0	--	1.55
Total	2.23	1.31	1.04	.17	.46	5.21*

C = Corn
SY = Soybeans
SU = Sunflowers
SB = Sugar Beets
SR = Sorghum

* 173.08 pixels (5.21% of all labeled pixels) were incorrectly labeled as to specific summer crop type but were correctly assigned to the summer crop land use group.

TABLE 2.24 DISTRIBUTION OF LABELING ERROR WITHIN SUMMER CROP LAND USE GROUP AS A % OF TOTAL # OF PIXELS CORRECTLY IDENTIFIED AS SUMMER CROPS BUT INCORRECTLY LABELED AS TO SPECIFIC CROP TYPE CORN BELT PERIPHERY SEGMENTS 185, 241, 1075, 1572 AND 1591

GROUND DATA

ANALYST	C	SY	SU	SB	SR
C	--	16.75	15.88	.00	6.64
SY	12.60	--	3.47	1.73	2.02
SU	.87	7.51	--	1.44	.00
SB	.00	.58	.58	--	.00
SR	29.35	.58	.00	.00	--
					100.00*

C = Corn
SY = Soybeans
SU = Sunflowers
SB = Sugar Beets
SR = Sorghum

* 100% of 173.08 incorrectly labeled pixels (5.21% of all labeled pixels).

Line	Point	Pixel P or M	Land Use Group	Crop Label	Alternate Label(s)	Confi-dence	Reason for Label Assignment
20	40	P	SC 1	C1	SY	2	temp. pattern, crop cal., grabs peak 25-30
	50	P	[illegible] 1	[illegible]			
	60	P	SC 1	C1	SY	2	"
	70	P	SC 1	C1	APR	2	" low grabs
	80	P	[illegible] 1		SSG		
	90	P	SSG		APR		
	100	P	SC 1	C1	SY	2	"
	110	P	SC 1	C1	SY	2	"
	120	P	SC 1	C1	APR	2	temp. pattern, low grabs
	130	P	SC 1	C1	APR	2	"
	140	P	SC 1	C1	APR	2	"
	150	P	SC 1	SY1	C	3	", but grabs > 35, TC > 70
	160	P	SC 1	SY1	C	3	" " "
	170	P	[illegible] 1	[illegible]			
	180	P	SC 1	C1	APR, D	2	temp. pattern, too narrow for registration
	190	P	I				
30	10	P	SSG				
	20	P	SC 1	C1	APR	2	temp. pattern, lower TC
	30	M		P-D/SSG			
	40	P	[illegible]				
	50	P	SC	C	APR	2	"
	60	P	APF 1				

Figure 2.1 Answer Sheet from Analyst A, Segment 241

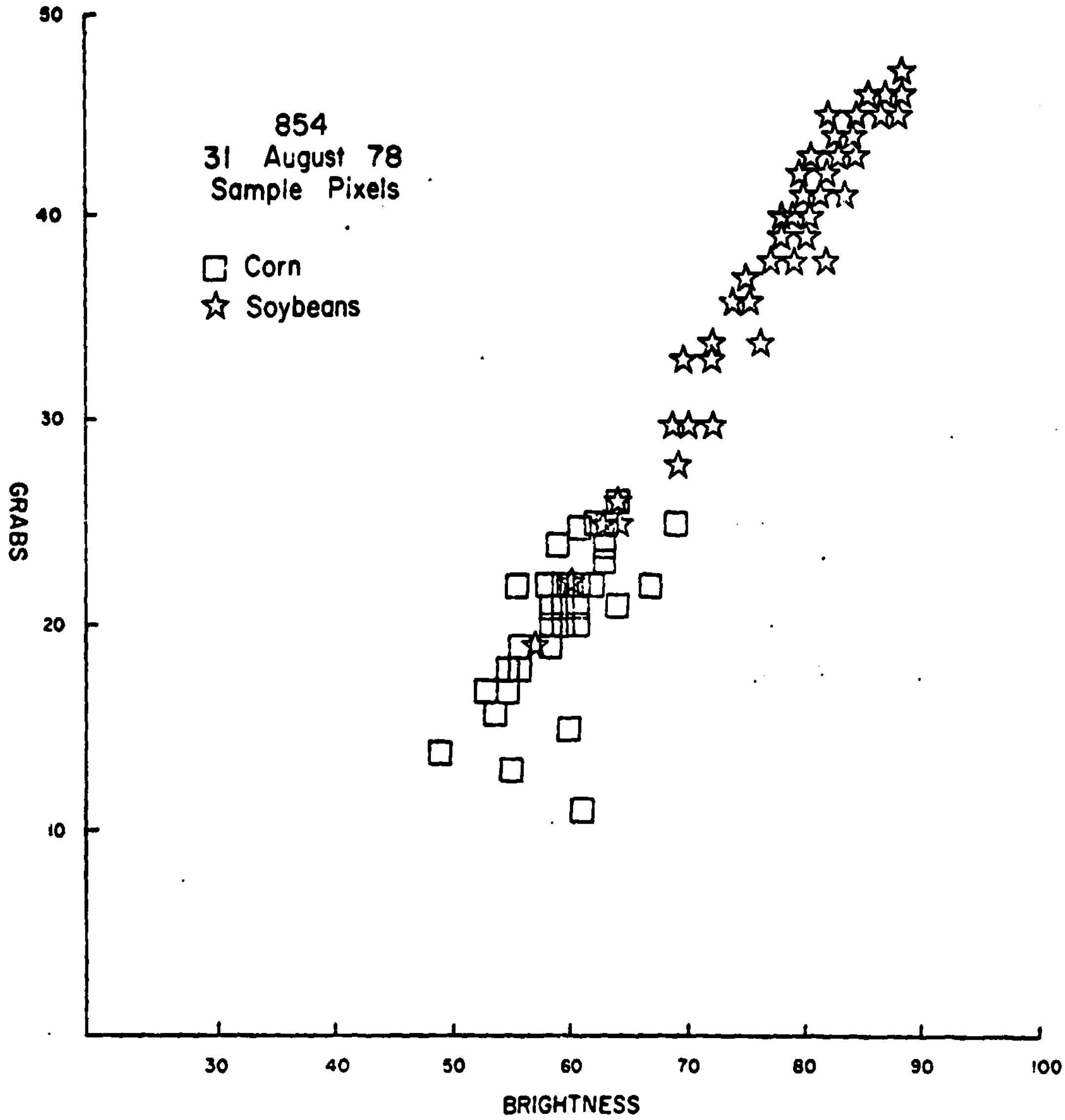

Figure 2.2

GRABS versus Tasselled Cap Brightness, (TC1) Tippecanoe County, Indiana. The symbols represent the extent of pure corn and soybean pixel distributions, extracted from a 209 dot sample. Point density is not indicated. Soybeans (pod setting to seed filling) are predominantly higher in GRABS and TC1 than corn (dough to dent) on this acquisition. However, a few pixels from less vigorous soybean fields fall into the corn distribution.

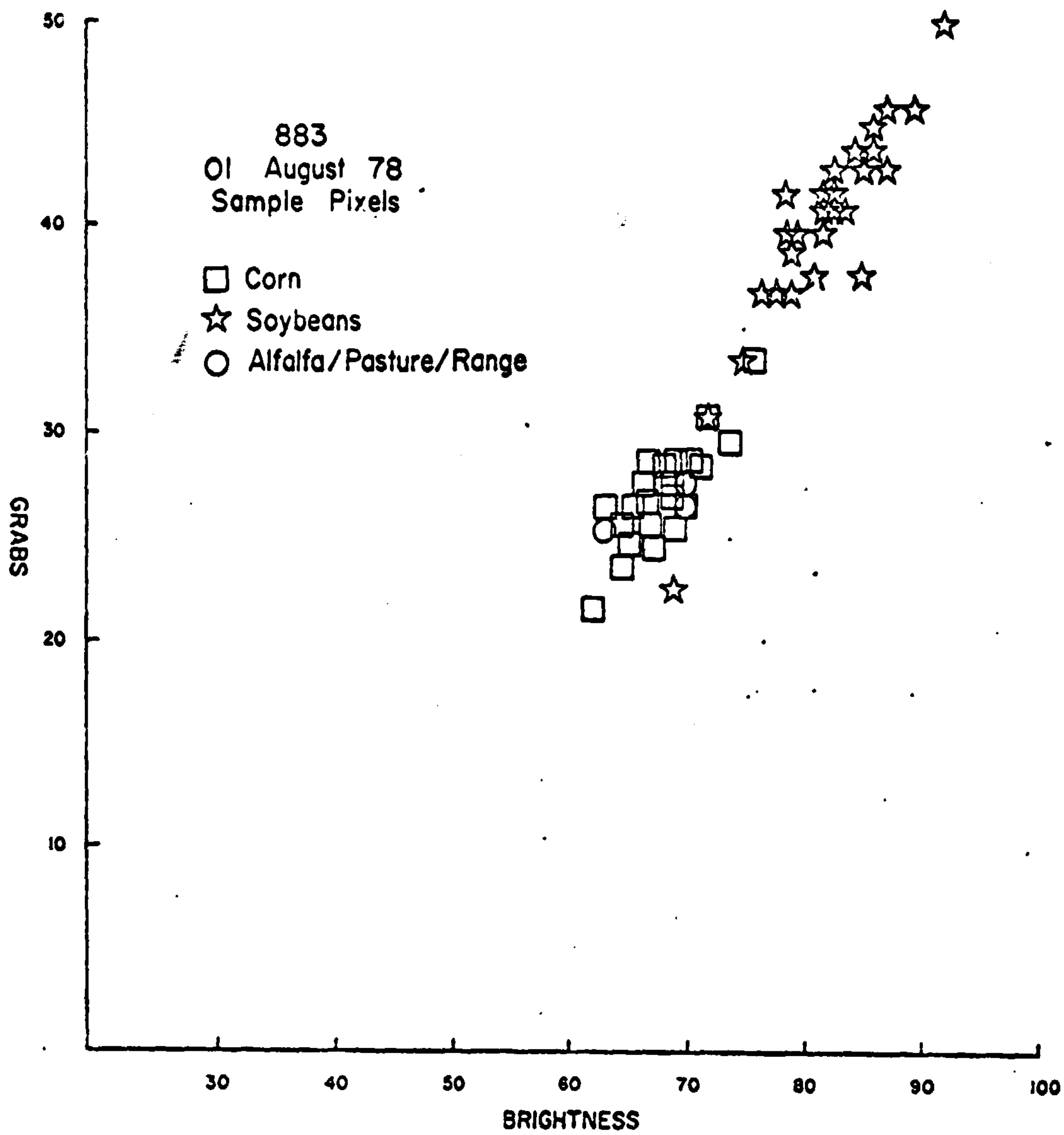

Figure 2.3

GRABS versus Tasselled Cap Brightness, Palo Alto County, Iowa. The symbols represent the extent of pure corn and soybean pixel distributions, extracted from a 209 dot sample. Point density is not indicated. Although corn (tasseling to silking) and soybeans (blooming to pod setting) are largely separable on this acquisition, some overlap does occur between the two crops. Several pixels that were identified as pasture and hay from ground data fall into the corn distribution.

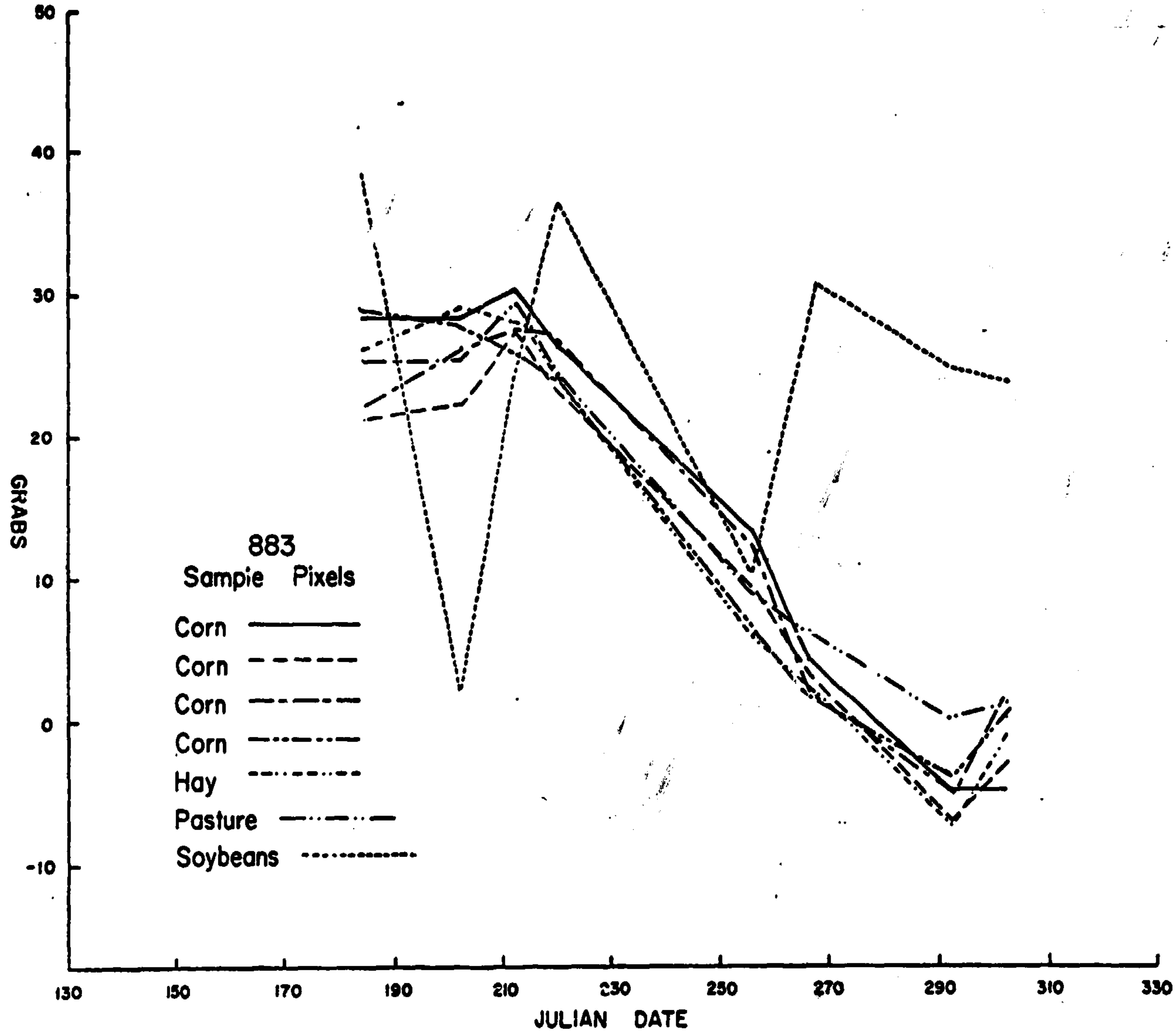

Figure 2.4

GRABS temporal plots of pure sample pixels, Palo Alto County, Iowa. The pasture and hay pixels, which fall into the corn GRABS versus TC1 distribution in the preceding figure, are temporally similar to corn. The soybean pixel follows an erratic temporal pattern characteristic of alfalfa, the dips in the curve corresponding to alfalfa cutting dates compiled from Iowa ESCS weekly crop reports. Temporal pattern is usually sufficient for separating pasture and hay from summer crops. There is some question as to the accuracy of the ground data labels for these three pixels.

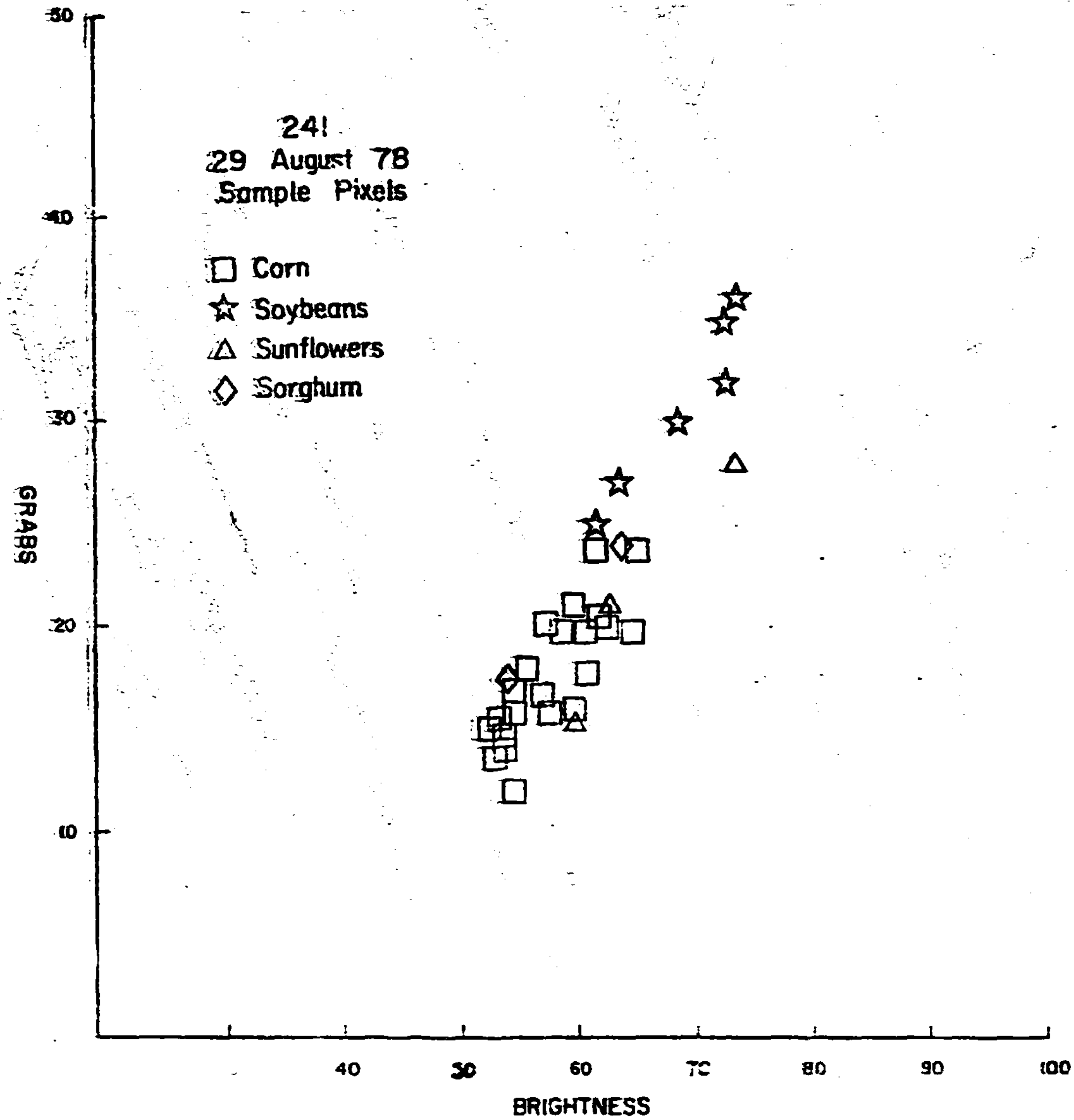

Figure 2.5

GRABS versus Tasselled Cap Brightness, Deuel County, South Dakota. The symbols represent the extent of pure corn, soybean, sunflower and sorghum pixel distributions, extracted from a 209 dot sample. Point density is not indicated. The general spectral relationships that were observed between corn and soybeans in the central Corn Belt pertain to this periphery segment as well. However, the boundary between the two distributions on this acquisition is less clear-cut than in the central Corn Belt (corn is in the blister to dent stage, soybeans are setting pods). Some confusion of sorghum and sunflowers with corn is also apparent.

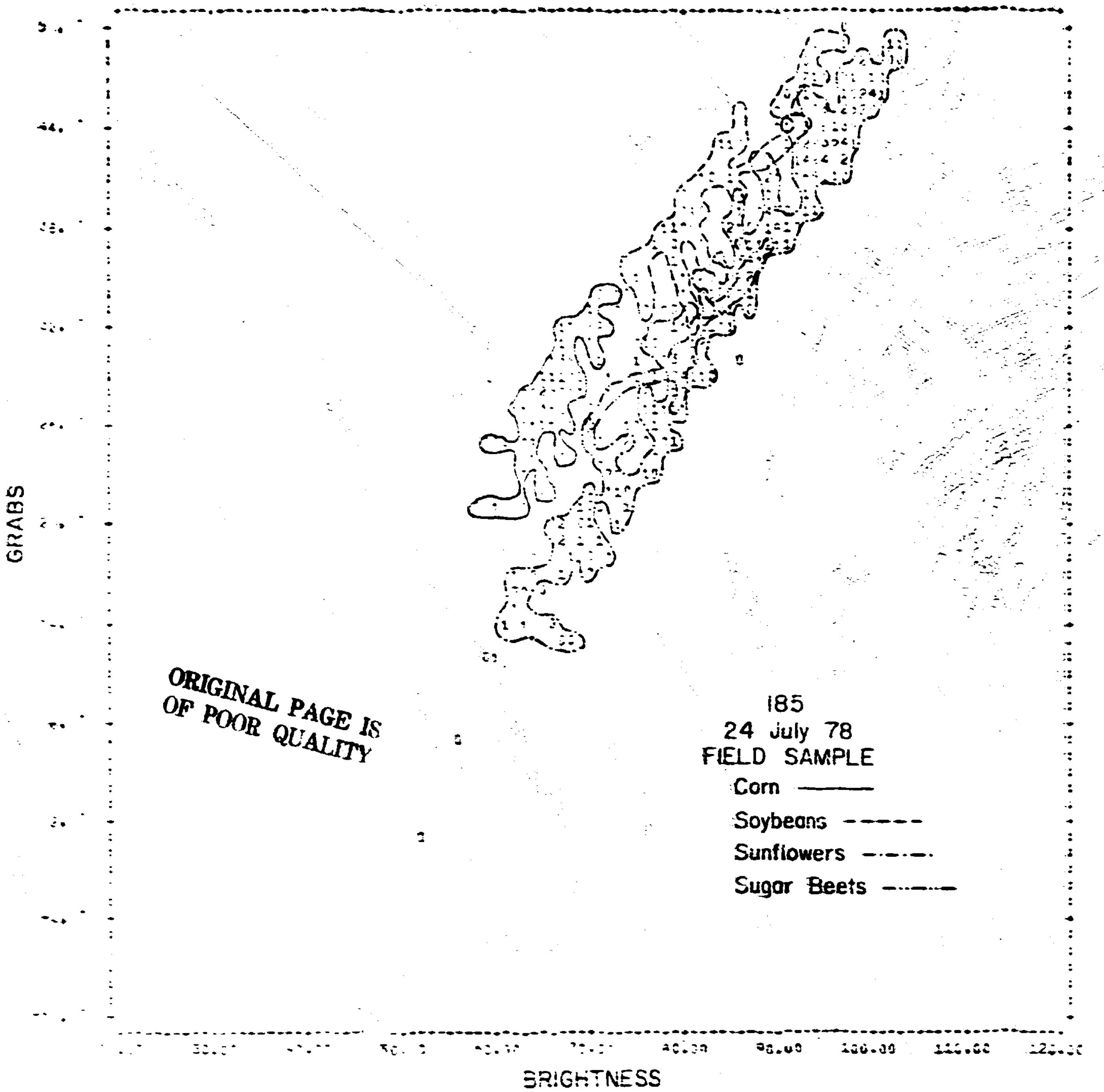

Figure 2.6

GRABS versus Tasselled Cap Brightness, Traverse County, Minnesota. The characters represent pure pixels from corn, soybean, sunflower and sugar beet sample fields. Point density is indicated by the magnitude of the numbers (character interval = 3). Sunflowers (blooming) and sugar beets (green canopy) occupy a green arm that is brighter than and approximately parallel to the green arm occupied by corn (tasseling) and soybeans (blooming). Soybeans are largely separable from corn based on relative GRABS values. Sunflower pixels with relatively low GRABS values are separable from corn based on relative brightness. Separability between sunflowers and soybeans based on relative brightness is more pronounced on a later acquisition. Separation of sugar beets from sunflowers appears to depend on temporal criteria rather than these spectral features.

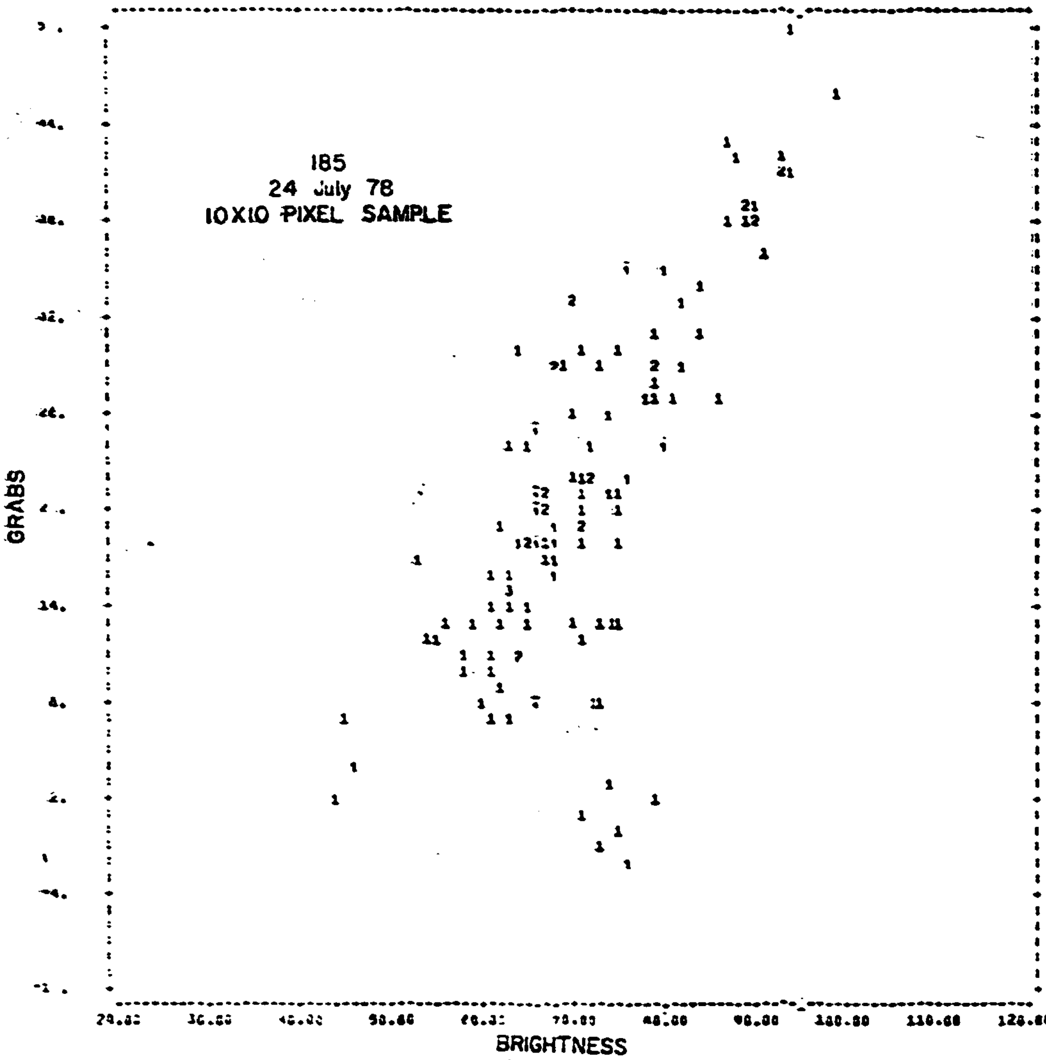

Figure 2.7

GRABS versus Tasselled Cap Brightness, Traverse County, Minnesota. This scatter plot, generated from a ten-by-ten pixel sample limited to probable summer crop strata, is of the type provided to all analysts in the interpretation test. Compare this scatter plot to that in the preceding figure, which was generated using a more intensive sample of summer crop fields. The ten-by-ten sampling rate is not sufficient for detection and discrimination of the four crops, which do not have large segment proportions.

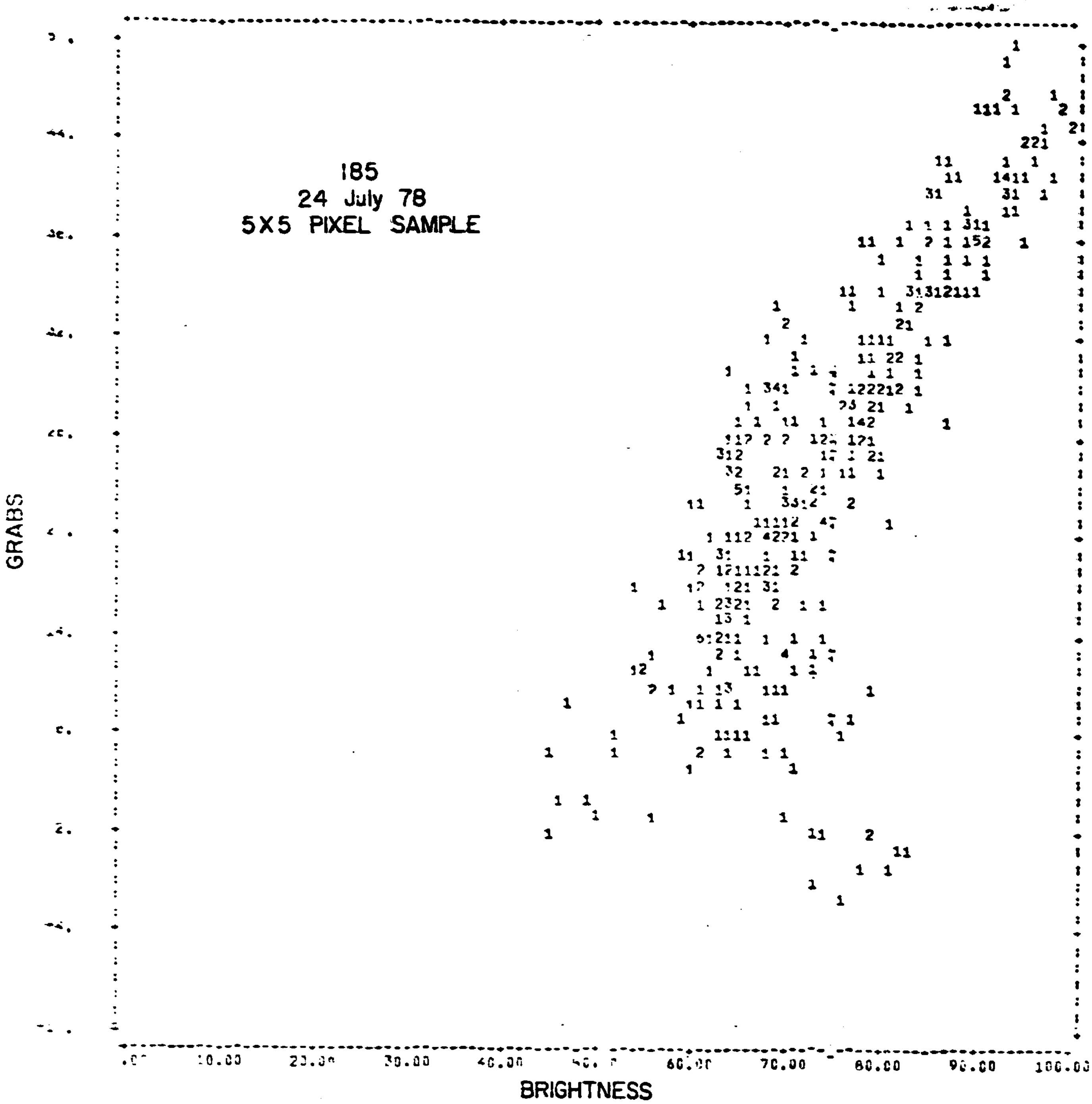

Figure 2.8

GRABS versus Tasselled Cap Brightness, Traverse County, Minnesota. This scatter plot was generated from a five-by-five pixel sample limited to probable summer crop strata. Discriminability of the crops is enhanced by this more intensive sample, which better displays the structure of the data. The parallel sunflower and corn-soybean arms are more apparent here than in the previous figure.

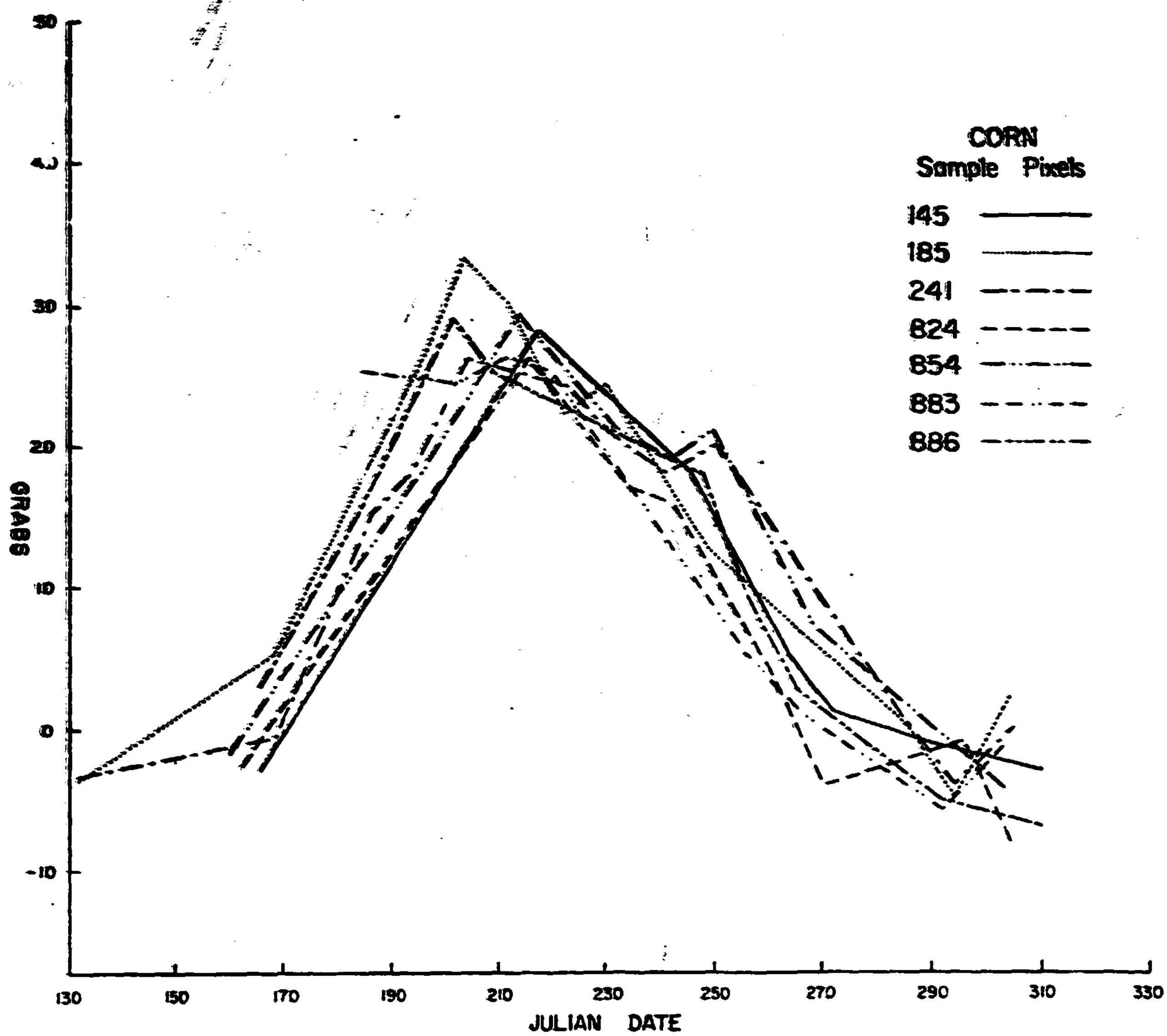

Figure 2.9

GRABS temporal plots of pure corn sample pixels from seven corn/soybean segments. Note the similarity of the curves. The corn curves appear to have a flatter overall appearance than soybean curves, often with a plateau or secondary peak after the maximum GRABS peak.

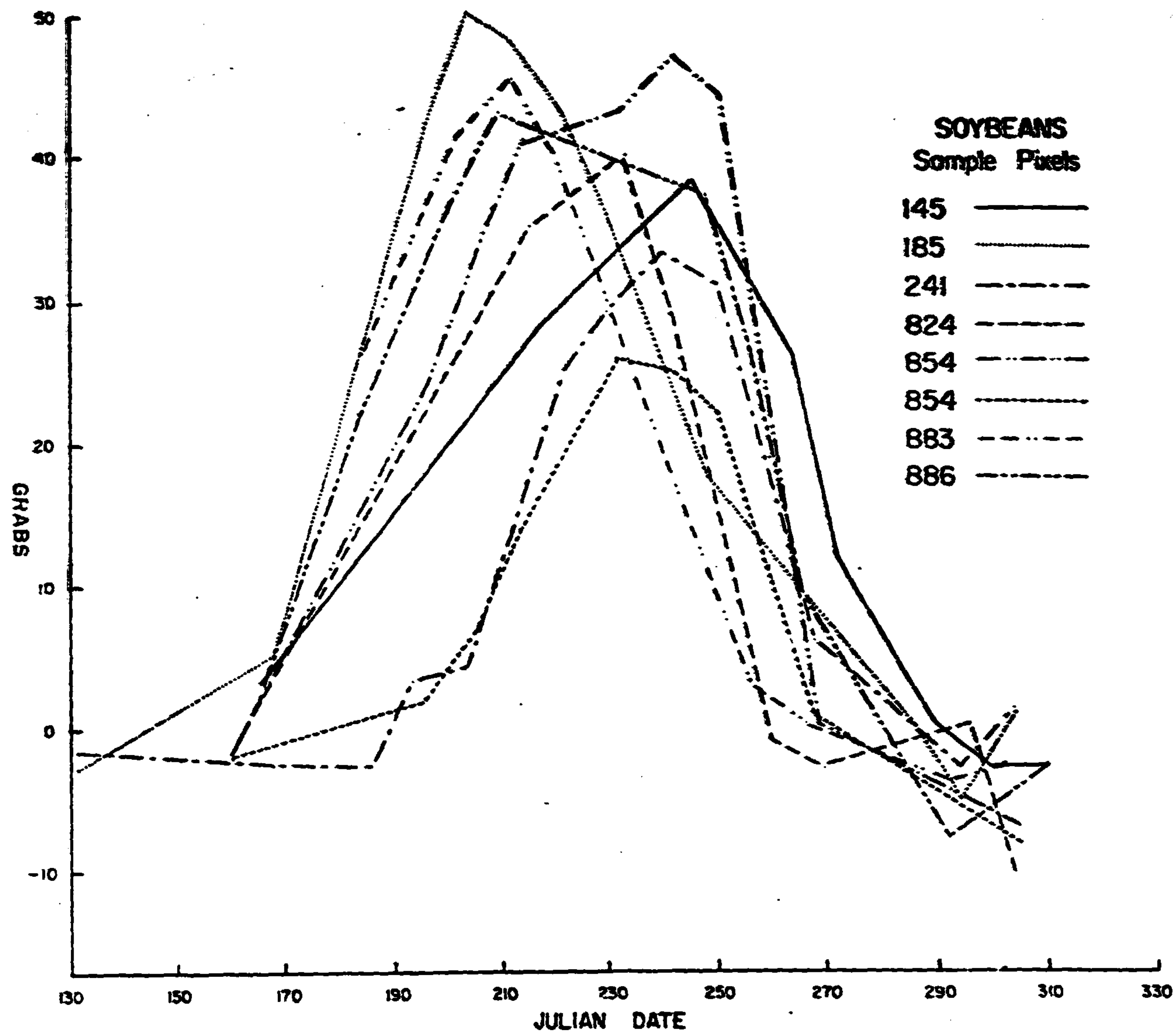

Figure 2.10

GRABS temporal plots of pure soybean pixels from seven corn/soybean segments. There appears to be more variability among soybean curves than among corn. The soybean curves tend to have higher maximum amplitudes and steeper sides. The later-developing soybean pixels (241 and 854) have very rapid rates of fall-off from peak reflectance despite the relatively low GRABS values attained at the peak.

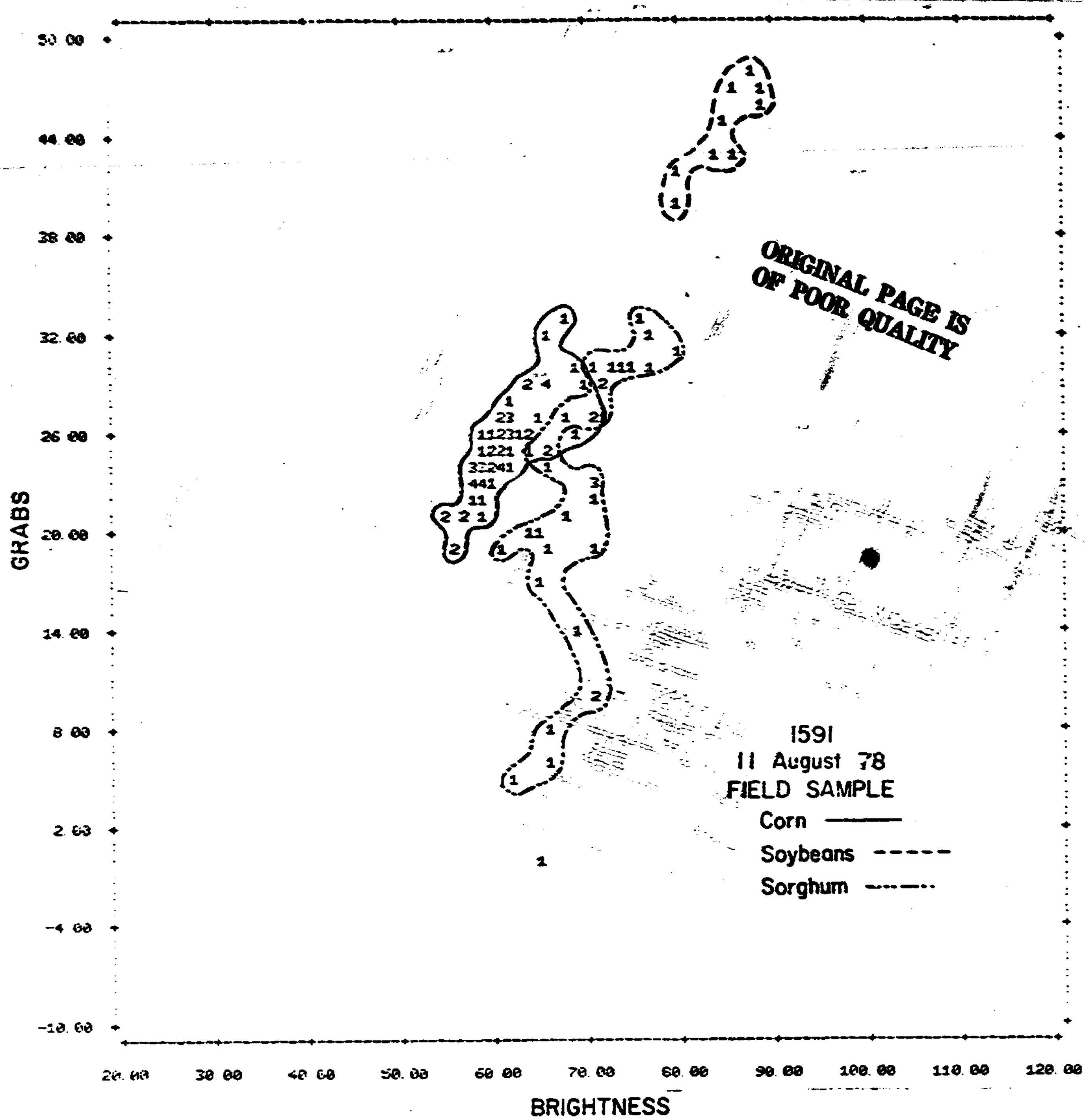

Figure 2.11

GRABS versus Tasselled Cap Brightness, Webster County, Nebraska. The characters represent pure pixels from corn, soybean and sorghum sample fields. Point density is indicated. Soybeans are clearly separable from corn and sorghum. Although sorghum is generally brighter than corn on this acquisition, there is sufficient overlap in the two distributions that the analyst cannot separate the crops with confidence.

2.4 SUBTASK B: EXTENSION OF DELTA FUNCTION STRATIFICATION PROCEDURE TO CORN AND SOYBEANS

2.4.1 OBJECTIVE

To modify and refine the Delta Function Stratification Procedure (DFS) which was developed for stratifying unlabelled clusters into small grains probability strata.

2.4.2 APPROACH

The Delta Function Stratification Procedure was first developed by UCB to stratify a segment into small grains probability strata. Using the ISOCLAS clustering program (UCB's adaptation of JSC's ISOCLS), a segment was first clustered on up to 16 channels (4 acquisitions) of Landsat untransformed data. A maximum of 60 clusters are possible with the current program, and each cluster is defined by a mean and standard deviation for each channel data. Following clustering the 7/5VI(2XMSS7/MSS5) green vegetation indicator is calculated for each acquisition for each cluster using the cluster means of the appropriate bands. A reference value of 7/5VI = 1.10 is used as a threshold of detection (soil line) value for green vegetation. Each cluster is assigned to a small grains probability stratum based on its temporal pattern of green canopy presence (values above 1.10) across the clustered acquisitions. The assignment is done by an analyst using crop calendar and other ancillary data. A full description of the original DFS procedure is contained in Hay, et. al., 1977.

The modifications and refinements to DFS that were of interest during the Fiscal Year 1979 (FY79) contract period included the following:

1.) extension of DFS to corn and soybeans and multicrop in general

2.) improvement in cluster purity relative to ground class, and/or improvement in strata average purity by minimizing boundary and mis-registered pixel effects

3.) minimize temporal variation within the clusters or develop relatively pure temporal classes directly

4.) increase the number of acquisitions that could be processed.

Two different approaches were pursued to address the above listed areas of interest. One approach involved the use of a spacial clustering algorithm to help eliminate boundary and misregistration

pixels from further spectral clustering. ~~The other approach required~~ no clustering of the data, but involved application of the DFS procedure to each pixel directly instead of to cluster means.

1.) Segments used to develop refinements to DFS were drawn from LACIE small grains segments with a diversity of other crop types and 2.) 1978-Corn Belt (corn-soybeans) segments also with a fair amount of crop type diversity. Maximizing crop type diversity was desirable to insure that the modified DFS procedure would be completely applicable to a multicrop environment regardless of crop type of interest. All spectral data was sun angle and haze corrected using Environmental Research Institute of Michigan's (ERIM) XSTAR haze correction algorithm.

<u>DFS WITH SPACIAL CLUSTERING</u>

Two spacial-spectral clustering algorithms were acquired for consideration with DFS. The first algorithm was BLOB developed by ERIM. The second algorithm was AMOEBA developed by Texas A&M University. Due to resource constraints, however, only BLOB has been implemented at this time at UCB on a CDC 7600 computer and evaluated with DFS. Along with the BLOB algorithm, ERIM also provided BLOB means and supplemental data for segment 1663 so that comparisons between the results of the algorithm as implemented at ERIM and UCB could be made.

Two modifications were made to BLOB in the process of implementing it at UCB. The algorithm as implemented at UCB has been called Son of BLOB (SOB).

The first modification to BLOB involved the use of a new distance measure. The new distance measure "SQUARE" is a modified infinity norm calculated as follows:

$$D = MAX\ ((X_B - X_A)^2 / P_{VAR}, (Y_B - Y_A)^2 / L_{VAR}, (B_1 - P_1)^2 / VARI_1, \ldots, (B_n - P_n)^2 / VAR_n)$$

where B = BLOB SPECTRAL VALUES

X_B, Y_B = BLOB CENTER CO-ORDINATES

P = PIXEL SPECTRAL VALUES

X_A, Y_A = PIXEL COORDINATES

The "SQUARE" distance measure produces blobs in which the variation among bands is minimized and blobing occurs on the basis

of the maximum variation in any one band. ERIM's BLOB distance measure, (modified Euclidean norm) blobs on the basis of the sum of the variation of all bands.

The second modification to BLOB consisted of increasing the band variation tolerance. This was necessary due to a limitation in the number of blobs (255) that could be handled in any one run on the CDC 7600 system. To insure that an entire segment could be blobed in a single computer run, the band variation tolerance was increased. The effect of the increased band variation tolerance on the SOB output was a BLOB map with fewer blobs and fewer excluded pixels.

To evaluate improvements in cluster purity and the implications to DFS, a comparison of DFS applied to clustering results achieved from 1.) ISOCLAS alone (ISOCLAS-DFS Procedure) and 2.) ISOCLAS applied after BLOBing (SOB) and stripping of non blob-center pixels, (SOB-ISOCLAS DFS Procedure) was made on segment 1663.

Segment 1663 was clustered using ISOCLAS on four acquisitions: 23 June 1977, 12 July 1977, 30 July 1977, and 17 August 1977. The DFS procedure was then applied to group the resultant clusters into crop group strata. These crop group strata were: 1.) Small grains (High Probability Small Grains Stratum), 2.) Alfalfa, Pasture, Range (Medium Probability Small Grains Stratum), 3.) Summer crops (Low Probability Small Grains), 4.) Fallow (Low Probability Small Grains) and 5.) Unassignable (Low Probability Small Grains). The unassignable stratum is for temporal pattern classes which are not clearly assignable to one of the other strata. These classes often turn out to be alfalfa, or pasture, or misregistered pixel classes.

The 7/5VI was used as the vegetation indicator to track the temporal pattern of each cluster. The vegetation detection threshold value of 1.10 was used as the reference point to determine the presence or absence of green vegetation on a given acquisition. Crop calendar data, of course, was critical to the DFS analysis. (See Hay, et. al., 1977 for a full description of the DFS procedure.) The results of the ISOCLAS clustering and subsequent crop group stratification using DFS are shown in Figure 2.13 and Table 2.25.

In the second procedure evaluated (SOB-ISOCLAS-DFS), segment 1663 was BLOBed by applying SOB to two acquisitions: 23 June and 30 July. A pixel was included within a blob center if it was spectrally similar to the pixels above, below, and to either side. Preliminary tests of BLOB during implementation showed that BLOBing on four acquisitions created too many BLOBs and the loss of too many pixels to stripping. Thus the decision was made to BLOB on only two acquisitions. The use of two acquisitions would theoretically eliminate, if not all, a substantial number of misregistered

pixels. Thus the number of pseudo-temporal patterns due to misregistration could be minimized. The remaining blob-center pixels were clustered using ISOCLAS on the same four acquisitions as in the ISOCLAS-DFS processing. The resultant clusters were grouped into crop group strata using the DFS procedure and the 7/5VI as the vegetation indicator. The results of the ISOCLAS-DFS processing compared with the SOB-ISOCLAS-DFS processing appear in Figure 2.14 and Table 2.26.

PIXEL-BY-PIXEL DFS

An alternative approach developed for applying DFS to a segment or larger area was the application of DFS on a pixel-by-pixel basis without going through clustering or BLOBing or any other pre-DFS pixel grouping process. A vegetation indicator was calculated for each pixel for each acquisition of registered sun angle and haze corrected Landsat data. In the pixel-by-pixel DFS (PxP-DFS) procedure, a green vegetation indicator that was based on ERIM's Tassel Cap transformation was used instead of the 7/5VI. The new vegetation indicator was called GRABS (Greenness Above Bare Soil). The GRABS vegetation indicator is the result of subtracting the 7/5VI = 1.10 (soil line) as projected from the Tassel Cap Greenness value of any pixel. ERIM supplied the equation (Greenness (TC2) = .0918 x Brightness (TC1) - 5.585) for the projection of the 7/5VI = 1.10 soil line onto Tassel Cap Greenness - Brightness plane. An average yellow stuff value and nonsuch value of -11.20 and 1.36 respectively were assumed. GRABS was then defined by GRABS = (TC2) - .0918 x (TC1) + 5.585 which can be represented as GRABS = .314 (MSS4) - .716 (MSS5) + .515 (MSS6) + .364 (MSS7) + 5.585 in Landsat MSS coordinates. GRABS values less than or equal to zero indicate non-detectable green vegetation, post-harvest conditions or bare soil. GRABS values greater than zero indicate the presence of detectable green vegetation or "turning" vegetation not yet harvested.

TEMPORAL PATTERN CLASS (TPC) EXTRACTION

For PxP-DFS, GRABS values for each pixel are produced for each acquisition. The GRABS bands for up to seven acquisitions are selected and a linear discriminant is placed within each GRABS band for the selected acquisitions. The linear discriminant is currently placed at a value of GRABS = 2. All values of GRABS below 2 are assigned a 0 value and considered non-vegetated, all values above GRABS = 2 are assigned a 1 value and considered vegetated. GRABS equal to 2 was chosen instead of 0 for the DFS stratification because some harvested fields of small grains don't go below GRABS = 0, but are generally below 2. Each pixel is then classified according to the binary pattern of 0 or 1 across all selected acquisitions. When the linear discriminant values for a given registered pixel are combined across all selected acquisitions, a binary number is generated

that represents the temporal pattern of that pixel relative to detectable vegetation above the GRABS vegetation threshold (GRABS = 2 in this case). The resultant classes represent the actual temporal pattern classes (TPC) present within the segment. The resultant temporal pattern classes are grouped and assigned to appropriate crop group strata similar to the manner in which clusters were grouped and labeled as to crop group strata in ISOCLAS-DFS.

Table 2.27 is an example of a tabular histogram of temporal pattern classes for segment 1572. This PxP-DFS classification was run on five GRABS bands for the five acquisitions: 14 May 1977, 2 June 1977, 20 June 1977, 8 July 1977, and 25 July 1977. The binary number which corresponds to the step level value (e.g. 00100 = step value 4) is the actual temporal pattern for pixels within temporal pattern class 4.

Assignment of the temporal pattern classes to crop group strata proceeded as follows. The temporal pattern classes were assigned to crop group strata using similar interpretation procedures as used in ISOCLAS-DFS. Crop calendar information and other ancillary data, and the product 1 imagery were used to calibrate the ancillary data to the specific segment being processed. Some slight modifications in the stratification procedure were made for PxP-DFS. These modifications involved temporal pattern class differentiation based on quality of the temporal pattern class as well as the actual temporal pattern. Four different qualities of temporal pattern classes were differentiated. These were:

(1.) Pure Temporal Pattern Classes. These were classes that had no significant misregistration "hits" in evidence within the pattern, or patterns that matched expected temporal patterns for the major crop groups expected to be present within the segment. Thus a pattern such as 001110, or 011100 would be considered pure since during the obvious vegetated phase (values of 1) there were no reversals to bare soil states. Alfalfa patterns may have some reversal such as 001101 or 011011 but these reversals would have to closely correspond to cutting operations as indicated in crop calendar data to be considered pure temporal patterns.

(2.) "A" Subclasses. These were temporal pattern classes that were off by only one "hit" from a "pure" temporal pattern class. For example 010110 would be only one hit off from 011110. Thus 010110 would be considered to be an "A" subclass of "pure" temporal class 011110.

(3.) Unassignable Classes ("B" classes). These were temporal pattern classes that were off by two or more "hits" from a "pure" temporal pattern class. These classes were considered

"unassignable" and were assigned to their own group stratum.

(4.) "Trivial" Temporal Pattern Classes. Classes with less than 50 pixels were considered to be trivial temporal pattern classes and were not assigned to individual crop group strata. These classes were mostly considered to be due to pixels that were misregistered. The trivial temporal classes were grouped into their own trivial Temporal Pattern Classes Stratum. The total number of pixels assigned to the trivial temporal patterns stratum was usually less than 5% of the segment and more frequently less than 2% of the segment. In assigning TPC's to crop group strata:

1.) First, trivial classes were grouped and assigned to the Trivial Temporal Patterns Stratum.

2.) Second, the "pure" temporal pattern classes were determined and assigned to their appropriate crop group strata.

3.) Third, the "A" Subclasses were determined, associated with the proper "pure" temporal pattern class of which they were subclasses, and finally assigned to the appropriate crop group stratum.

4.) Fourth, the Unassignable ("B") Temporal Classes were determined. If an interactive display system was not used during the interpretation to assign the temporal pattern classes to crop group strata, then the "B" classes were grouped together and assigned to their own Unassignable Group Stratum. If an interactive display system was used during the PxP-DFS interpretation, then the "B" classes were associated with a "pure" temporal pattern class based on spacial relationships and assigned to the appropriate crop group stratum.

An example of a PxP-DFS stratification for segment 1572 is shown in Figure 2.16. Figure 2.17 is the crop calendar data used by the analyst to make temporal pattern class assignments for segment 1572 to Crop Group Strata.

2.4.3 RESULTS AND DISCUSSION

Segment 1663 was used to compare the three different implementations of DFS. These results can be seen in Figures 2.13 through 2.15, and Tables 2.28 through 2.31.

DFS APPLIED TO CLUSTERS (Spectral only vs. Spectral-Spacial)

In segment 1663, a total of 206 blobs were found using SOB. After stripping of non blob-center pixels only 6935 pixels (30% of segment) remained to be processed through ISOCLAS and subsequent DFS. Using the digitized wall-to-wall ground data for the segment, it was found that of the total 206 blobs, 156 (75.7%) blobs were pure relative to crop group and 109 (52.9%) blobs were pure relative to specific crop type. Thus 50 blobs were mixed relative to crop group and 97 blobs were mixed relative to crop type. Table 2.28 shows the distribution of blobs among crop types present.

A number of temporal pattern classes resultant from ISOCLAS-DFS without SOB were missing from the results of the SOB-ISOCLAS-DFS processing. Table 2.29 shows the resultant temporal pattern classes for both processing procedures. The missing temporal pattern classes probably represent pseudo-temporal patterns resulting from pixel mis-registration and boundary conditions which were eliminated by the use of SOB.

Average cluster purity by crop group stratum weighted by the number of pixels within a cluster is presented in Table 2.30 for DFS with both clustering procedures. As can be seen, the average cluster purity for SOB-ISOCLAS-DFS, where only blob centers were processed through ISOCLAS and DFS, is slightly higher in all crop group strata than the ISOCLAS-DFS cluster purities. This, of course, was expected. The average crop group stratum purity for ISOCLAS-DFS without SOB was 74.5% for all pixels in the segment. This was less than the average crop group stratum purity for SOB-ISOCLAS-DFS which was 93.6% for blob-center pixels only.

A comparison of variance reduction factors (R-values) between both DFS applied to clusters procedures for segment 1663 showed a reduction in the R-value from .496 for ISOCLAS-DFS to .110 for SOB-ISOCLAS-DFS. See Table 2.31.

The above results indicate that the performance of DFS can be improved when the effect of misregistration pixels is minimized. The large number of pixels rejected as not belonging to blob centers, however, was disturbing. In addition, processing was still limited to only four acquisitions. Therefore, an alternative processing procedure was evaluated which could potentially overcome the limitations of SOB-ISOCLAS-DFS, but still allow pure temporal pattern classes (TPC) to be extracted without contamination from misregistered pixels.

EVALUATION OF PxP - DFS

Segment 1663 was proceessed using PxP-DFS so that the results could be compared with the ISOCLAS-DFS and SOB-ISOCLAS-DFS results

for the same segment. Segment 1663 was processed twice using PxP-DFS, once with the GRABS threshold set at 0 for all six acquisitions processed and once with the GRABS threshold set at 0 for the first four pre-small grains harvest acquisitions and at 2 for the last two post-small grains harvest acquisitions. Temporal Pattern Class purities by crop group stratum and average strata purities were determined using the digitized ground data. These results are shown in Table 2.32. The variance reduction factor (R-value) was also calculated and compared to the ISOCLAS-DFS and SOB-ISOCLAS-DFS processing and is shown in Table 2.31.

Strata purities by crop group using only the pure temporal pattern classes in the stratification, compared very favorably with the cluster purities obtained using SOB-ISOCLAS-DFS. In addition, the number of pixels included in the stratification was over 50% of the segment as compared to 30% for SOB-ISOCLAS-DFS. When the A and B subclasses were added, the number of pixels stratified increased to 95.6%, however, strata purity for small grains and summer crops fell slightly to 91%.

Average class purity by crop group stratum ranged from a low of .23 for the alfalfa/pasture crop group stratum to 1.00 for the fallow crop group stratum. The small grains and summer crops crop group strata had average class purities ranging from .88 to .97. The low average class purity for the alfalfa/pasture stratum was due to commission of some summer crops to this stratum. The average class purity by crop group stratum for alfalfa/pasture could probably be improved if acquisitions more optimum for this crop group were selected for the various DFS processings. However, summer crops and small grains were given priority in the acquisition selection.

Variance reduction factors (R-values) for PxP-DFS (Table 2.31) were comparable to values obtained from ISOCLAS-DFS but higher than those from SOB-ISOCLAS-DFS. The inclusion of the A and B subclasses had the effect of lowering the R-value for segment 1663.

The R-values in Table 2.31 were calculated using digitized ground data. The range of R-values for segment 1663 was from .110 for the SOB-ISOCLAS-DFS processing to .512 for the PxP-DFS (Pure classes only, GRABS Threshold = 0). The low R-value of .110 for the SOB-ISOCLAS-DFS processing is somewhat misleading in that it must be remembered that only 30% of the pixels were processed after stripping and that 70% of the segment was disregarded. The next lowest R-value of .388 was obtained for the PxP-DFS (Pure classes + A + B, GRABS Threshold = 2 on last two dates). In this case 96.5% of the pixels were assigned to a crop group stratum and 3.5% of the pixels were assigned to the Trivial Temporal Patterns Stratum.

TEN TEST SEGMENTS

The ten test segments used in the corn/soybeans guidelines test in Subtask A were processed using PxP-DFS. The segments covered a wide range of corn/soybean growing conditions, some segments were almost exclusively corn and soybeans while others had a variety of crop types. All ten segments had good acquisition histories, and the GRABS bands were already available. The segments were processed through PxP-DFS using a GRABS threshold of two on all acquisitions.

At the time of analysis, digitized ground data was not available for these segments so that average class purities could not be accurately or easily determined. Thus, evaluation of PxP-DFS for these ten segments was confined to examining the variance reduction factors. Initially, variance reduction values were computed using ground data photos for the 209 grid intersections only. Subsequent to the analysis, digitized ground data became available and R-values were re-computed for the full segments. Both sets of variance reduction values are shown in Table 2.33. Using digitized ground data, the average R-value for PxP-DFS (pure classes +A + B) across eleven segments (segment 1663 + 10 additional segments) was .713 with a range from .296 to .963.

Mean variance reduction values for the ten segments decreased as the A and B subclasses were included in the stratification. The very high values (R-values) e.g. .960 segment 854 and .847 segment 824 are from segments composed almost entirely of corn and soybeans. In segment 824, 21002 pixels (92% of the segment) fell in pure temporal pattern classes of summer crop or subclasses of summer crop. Of the grid intersections called summer crop by PxP-DFS 86% were correctly classified. The high R-values for these segments resulted from the fact that the segments were composed of essentially a single stratum and thus little improvement over a random sample was possible. The segments with a variety of crop types, e.g. segments 1572, 1075, 185, had variance reduction values similar to segment 1663. Examples of the stratifications for these segments are shown in Figure 2.18.

2.4.4 SUMMARY AND CONCLUSIONS

In segment 1663, the highest average strata purity weighted by the number of pixels assigned to each stratum was achieved with the SOB-ISOCLAS-DFS procedure with an average strata purity of 93%. This procedure, however, assigned only 6935 pixels (30.2% of segment) to crop group strata since the remaining pixels had been eliminated in the stripping operation of SOB. The next highest average strata pruity was achieved with the PxP-DFS (GRABS threshold = 2 on last 2 dates) with an average strata purity of 77%. This procedure

assigned 22131 pixels (96.5% of segment) to crop group strata. Rating the procedures according to merit based on average strata purity and number of pixels within a segment assigned to a crop group stratum the various DFS processing procedures rank as follows:

Procedure Segment 1663	Merit Index	Average Strata Purity	Pixels Assigned #
PxP-DFS (Pure + A + B;G=2*)	16.9	.77	22259 (97.1%)
ISOCLAS-DFS	16.6	.73	22932 (100%)
PxP-DFS (Pure + A + B;G=0)	15.9	.74	21733 (94.8%)
PxP-DFS (Pure + A;G=2*)	14.4	.75	19183 (83.7%)
PxP-DFS (Pure + A;G=0)	13.6	.71	19320 (84.2%)
PxP-DFS (Pure only; G=2*)	8.9	.70	12838 (56.0%)
PxP-DFS (Pure only; G=0)	7.5	.62	12175 (53.1%)
SOB-ISOCLAS-DFS	6.4	.93	6935 (30.2%)

* GRABS threshold = 2 on last 2 dates

The evaluation of PxP-DFS indicated that the procedure had several advantages. It produced a stratification which could be output in image format. The color coded DFS stratification allowed misregistered and edge pixels to be identified in part based on spacial characteristics. The stratification was sufficient for use in stratified area estimation ISOCLAS procedures and valuable for producing advanced spectral aids. (See subtask 2.C, section 2.) The procedure was faster and cheaper than either DFS or SOB-ISOCLAS-DFS and also operated on a majority of the pixels in the segment.

1663 Richland, North Dakota 1977

DFS - ISOCLAS

Cluster	Cluster Means - 7/5 Ratio				Points	Class
	JN23	JL12	JL30	AG17		
1	2.97	3.46	2.76	2.22	791	SC
2	2.95	.85	.82	.94	37	SG
3	1.47	1.31	1.04	2.64	54	A
4	2.87	1.23	2.20	1.98	33	A
5	3.27	1.63	.95	1.13	815	SGA
6	2.36	3.16	2.49	2.36	963	SC
7	2.84	1.50	.92	1.01	840	SGA
8	2.14	2.76	2.25	1.95	407	SC
9	2.38	1.26	.95	.95	867	SGA
10	2.62	1.71	.98	.91	338	SGA
11	2.88	3.01	2.40	2.42	615	SCA
12	2.80	1.35	.93	.99	620	SGA
13	3.34	1.82	.96	1.05	747	SGA
14	1.56	2.65	2.30	2.52	742	SCA
15	3.16	2.66	2.20	2.48	919	P
16	.99	.99	.89	1.06	533	F
17	2.64	1.64	1.37	1.88	446	P
18	1.71	2.27	1.65	1.94	614	SCA
19	2.05	1.08	.87	.99	731	SG
20	1.82	2.25	2.52	3.53	614	SCC
21	2.88	2.26	2.43	2.26	227	A
22	2.27	.89	1.67	1.73	45	X
23	2.05	.95	1.28	1.53	46	X
24	2.28	.96	.88	1.00	148	SG
25	2.22	1.32	.94	1.05	532	SGA
26	2.02	1.06	.88	1.01	193	SGA
27	3.38	1.39	.92	.96	460	SGA
28	2.46	2.27	2.04	2.09	632	SCD
29	2.38	1.15	1.08	1.22	411	P
30	2.51	1.33	.94	1.01	818	SGA
31	1.31	1.42	1.08	1.18	354	P
32	2.94	2.24	1.21	1.23	649	P
33	2.41	1.03	.90	.98	753	SG
34	2.16	1.68	1.60	1.69	559	P
35	2.76	2.89	1.78	1.73	393	SCB
36	1.58	2.12	2.49	2.77	796	SCC
37	1.47	2.95	2.69	3.09	351	SCA
38	1.61	1.42	1.65	2.05	304	A
39	4.22	1.77	.88	.98	227	SGA
40	1.15	1.90	2.81	3.29	338	SCC
41	3.39	1.70	.98	.96	784	SGA
42	2.65	1.05	1.20	1.27	176	A
43	2.01	.98	.91	.99	76	SG
44	2.55	1.55	2.20	2.38	97	A
45	2.43	1.17	1.02	1.19	77	SG
46	2.64	2.29	1.68	1.15	36	SCD
47	2.00	.90	.84	.95	47	SG
48	3.15	2.75	2.17	1.72	323	SCD
49	2.31	1.11	.98	.96	123	SG
50	2.32	1.73	2.24	1.97	67	A
51	2.95	1.80	2.13	1.58	122	A
52	3.05	1.21	1.15	1.39	126	P
53	2.51	.98	.95	.97	207	SG
54	3.03	1.69	1.50	2.00	174	P
55	2.22	1.48	1.14	.91	42	X
56	3.31	1.43	2.12	1.60	48	A
57	3.13	2.41	2.17	1.56	252	SCD
58	3.12	2.70	2.03	.99	45	X
59	1.91	2.63	2.02	1.20	76	SCD
60	2.51	1.36	2.26	2.17	82	A

DFS - ISOCLAS

CLASS KEY

SG SGA	High Probability Small Grain
SC SCA SCB SCC SCD	Low Probability Small Grain
A P	Medium Probability Small Grain
F	Fallow
X	Unassignable/Misregistered

Table 2.25

Table 2.26

Segment 1663: 6 June, 23 June, 30 July, 17 August 1977

DFS (with and without BLOB) vs. Ground Data

DFS without BLOB

		SMGR	Sum. Cr.	P/A/G	Fal.	
Ground Data	SMGR	8831	771	2244	36	11882
	Sum. Cr.	176	6625	1467	11	8279
	P/A/G	176	292	330	3	701
	Fal.	176	80	151	483	890
	Other	104	262	814	0	1180
Total		9363	8030	5006	533	22932

DFS with BLOB

		SMGR	Sum. Cr.	P/A/G	Fal.	
Ground Data	SMGR	4018	44	76	0	4138
	Sum. Cr.	15	2144	163	0	2322
	P/A/G	7	44	41	1	93
	Fal.	39	21	0	165	225
	Other	13	27	117	0	157
Total		4092	2280	397	166	6935

Table 2.27

Tabular Histogram - Segment 1572

Histogram Table   Dir: JBO   File: 1572GRABS   Band 27   DFS(T=2)

Step Level	0	1	2	3	4	5	6	7
Binary Value	00000	00001	00010	00011	00100	00101	00110	00111
Count	190	116	67	652	91	97	103	1961
Percent	.8	.5	.3	2.8	.4	.4	.4	8.6
Cum Percent	.8	1.3	1.6	4.5	4.9	5.3	5.7	14.3
Step Level	8	9	10	11	12	13	14	15
Binary Value	01000	01001	01010	01011	01100	01101	01110	01111
Count	94	85	37	179	87	116	157	1313
Percent	.4	.4	.2	.8	.4	.5	.7	5.7
Cum Percent	14.7	15.1	15.2	16.0	16.4	16.9	17.6	23.3
Step Level	16	17	18	19	20	21	22	23
Binary Value	10000	10001	10010	10011	10100	10101	10110	10111
Count	23	18	11	43	31	29	76	500
Percent	.1	.1	.0	.2	.1	.1	.3	2.2
Cum Percent	23.4	23.5	23.5	23.7	23.9	24.0	24.3	26.5
Step Level	24	25	26	27	28	29	30	31
Binary Value	11000	11001	11010	11011	11100	11101	11110	11111
Count	52	77	47	156	153	311	917	15143
Percent	.2	.3	.2	.7	.7	1.4	4.0	66.0
Cum Percent	26.7	27.1	27.3	27.9	28.6	30.0	34.0	100.0

Table 2.28

Segment 1663: 1977 Data

SOB Purity: SOB vs. Ground Data

Crop Type	# BLOBS with Crop Type	# BLOBS with Crop Type Only
Spring Wheat	75	18
Barley	55	12
Oats	21	3
Flax	9	3
Small Grains	104	70
Sunflower	60	36
Soybeans	32	11
Sugar Beet	27	11
Sorghum	1	0
Corn	7	0
Summer Crops	104	68
Fallow	18	9
Pasture	19	2
Alfalfa	5	0
Trees	15	4
Other	7	0

Table 2.29

Segment 1663

Delta Function Stratification - Temporal Patterns

A	>1.1	+	>1.1	-	>1.1	-	>1.1	1198	(5)	*
B	>1.1	+	>1.1	+	>1.1	+	>1.1	1748	(8)	*
C	>1.1	-	>1.1	-	<1.1		<1.1	7241	(32)	*
D	>1.1	-	>1.1	-	>1.1	+	>1.1	2873	(12)	*
E	>1.1	+	>1.1	-	>1.1	+	>1.1	2322	(10)	*
F	>1.1	-	<1.1		<1.1		<1.1	2122	(9)	*
G	>1.1	-	>1.1	+	>1.1	+	>1.1	455	(2)	*
H	>1.1	-	>1.1	+	>1.1	-	>1.1	569	(2)	*
I	<1.1		<1.1		<1.1		<1.1	533	(2)	*
J	>1.1	-	>1.1	-	>1.1	-	>1.1	1319	(6)	*
K	>1.1	-	>1.1	-	<1.1	+	>1.1	842	(4)	
L	>1.1	+	>1.1	-	>1.1	-	>1.1	1356	(6)	
M	>1.1	-	<1.1	+	>1.1	+	>1.1	176	(1)	
N	>1.1	+	>1.1	-	<1.1	+	>1.1	91	(1)	
O	>1.1	-	>1.1	-	>1.1	-	<1.1	87	(1)	
P	<1.1	+	>1.1	+	>1.1	+	>1.1	**		

*Temporal patterns present whem SOB mask used

**Temporal pattern present only whem SOB mask used

Table 2.30

Segment 1663: 1977 Data

Average DFS Cluster Purity with and without SOB Mask

with SOB

	By Crop	Crop Group	Pts.
Small Grains	.76	.97	4092
Summer Crops	.79	.94	2280
Fallow		.99	166
Alfalfa/Pasture		.39	397
		Total	6935

without SOB

	By Crop	Crop Group	Pts.
Small Grains	.64	.92	9363
Summer Crops	.57	.82	8030
Fallow		.91	5006
Alfalfa/Pasture		.22	533
		Total	22932

Table 2.31

Segment 1663: 1977 Data

Variance Reduction (R-Value)

	R
ISOCLAS-DFS	.496
SOB-ISOCLAS-DFS	.110
Pixel-by-Pixel DFS	
Threshold = 0	
Pure classes only	.512
Pure + "A" subclasses	.467
Pure + "A" and "B" subclasses	.431
Pixel-by-Pixel DFS	
Threshold = 2.0	
Pure classes only	.397
Pure + "A" subclasses	.391
Pure + "A" and "B" subclasses	.388

Table 2.32

Segment 1663: 1977 Data

Average Class Purity: Pixel-by-Pixel DFS with GRABS Data (6 dates)

	Pure Classes			Pure + "A"			Pure + "A" and "B"		
	by crop	crop group	pts.(%)	by crop	crop group	pts.(%)	by crop	crop group	pts.(%)
All Dates Threshold = 0									
Small Grains	.71	.95	4086	.68	.95	6695	.64	.95	8882
Summer Crops	.74	.97	2283	.61	.88	6819	.62	.88	6925
Fallow		1.00	79		1.00	79		.96	201
Alfalfa/Pasture		.23	5727		.23	5727		.23	5727
Total			12175 (53.1)			19320 (84.2)			21735 (94.8)
Last Two Dates Threshold = 2.0									
Small Grains	.71	.96	5581	.67	.93	7529	.71	.92	10323
Summer Crops	.74	.97	2274	.60	.89	6620	.60	.89	6724
Fallow		1.00	90		1.00	141		.86	319
Alfalfa/Pasture		.27	4893		.27	4893		.27	4893
Total			12838 (56.0)			19183 (83.7)			22259 (97.1)

Table 2.33

Variance Reduction - Pixel-by-Pixel DFS

209 Dots

Segment		Pure	P + A	P + A + B
145		.872	.872	.824
185		.594	.625	.552
241		.714	.765	.737
824		.696	.810	.866
854		.997	.987	.986
883		.479	.709	--
886		.456	.480	.503
1075		.606	.584	.602
1572		.394	.483	.573
1591		.899	.782	.596
	$\bar{x}$	.697	.710	.693

Full Segment

Segment		Pts.	Pure	Pts.	P + A	Pts.	P + A + B
145		11444	.752	14785	.871	16693	.848
185		7817	.762	14440	.765	18594	.654
241		11360	.787	18493	.819	21169	.754
824		3737	.659	13635	.825	21211	.847
854		17827	.882	21596	.963	21993	.960
883		15712	.685	19522	.685	---	.685
1075		9579	.599	12005	.597	12713	.623
1572		17921	.296	20479	.457	21930	.499
1591		13148	.792	17899	.697	21641	.716
1663		12838	.397	19183	.391	22259	.388
	$\bar{x}$	12180	.659	17532	.713	19943	.705

Figure 2.12

Segment 1663
Ground Data 1977

Key

red = summer crops
purples = small grain
cyan = trees
dark green = pasture/alfalfa
black = fallow
grey = water/homestead/
field problem

Figure 2.13

Segment 1663
DFS ISOCLAS

Key

purples = high probability small grain

dark green
blue green = medium probability small grain
cyan

orange
red orange = low probability small grain
yellow

brown = fallow

black = unassignable

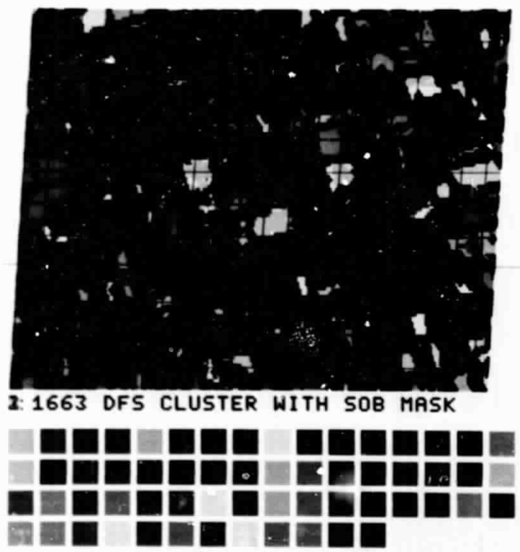

Figure 2.14

Segment 1663 - DFS with SOB mask

purples = high probability small grain

cyan, dark green = medium probability small grain

brown, yellow, orange, red = low probability small grain

black = ...low and stripped pixels

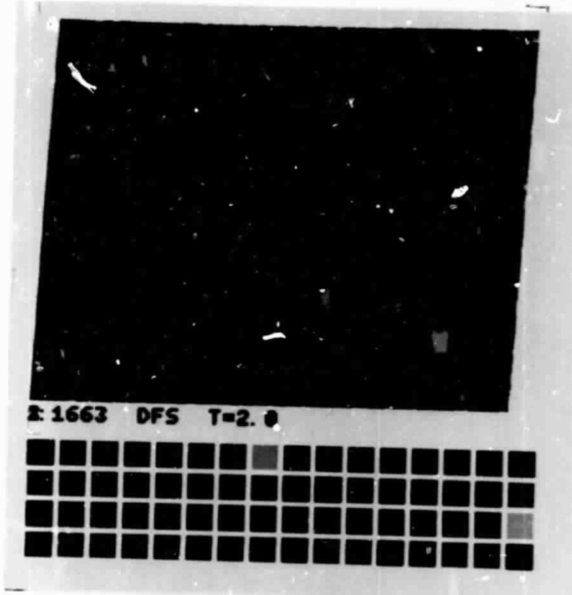

Figure 2.15

Segment 1663 - Pixel-by-Pixel DFS with GRABS Data
Vegetation Threshold = 2.0 on all dates

purples = small grain

orange, red, yellow = summer crops

cyan = alfalfa/pasture

green = pasture

black = fallow

grey = unassigned

Figure 2.16

Segment 1572 - Pixel-by-Pixel DFS
Five Dates of GRABS Data
Vegetation Threshold = 2.0 on all Dates

red = summer crops
cyan = alfalfa/pasture
green = pasture
purple = small grains
black = fallow
grey = unassignable
(trivial classes)

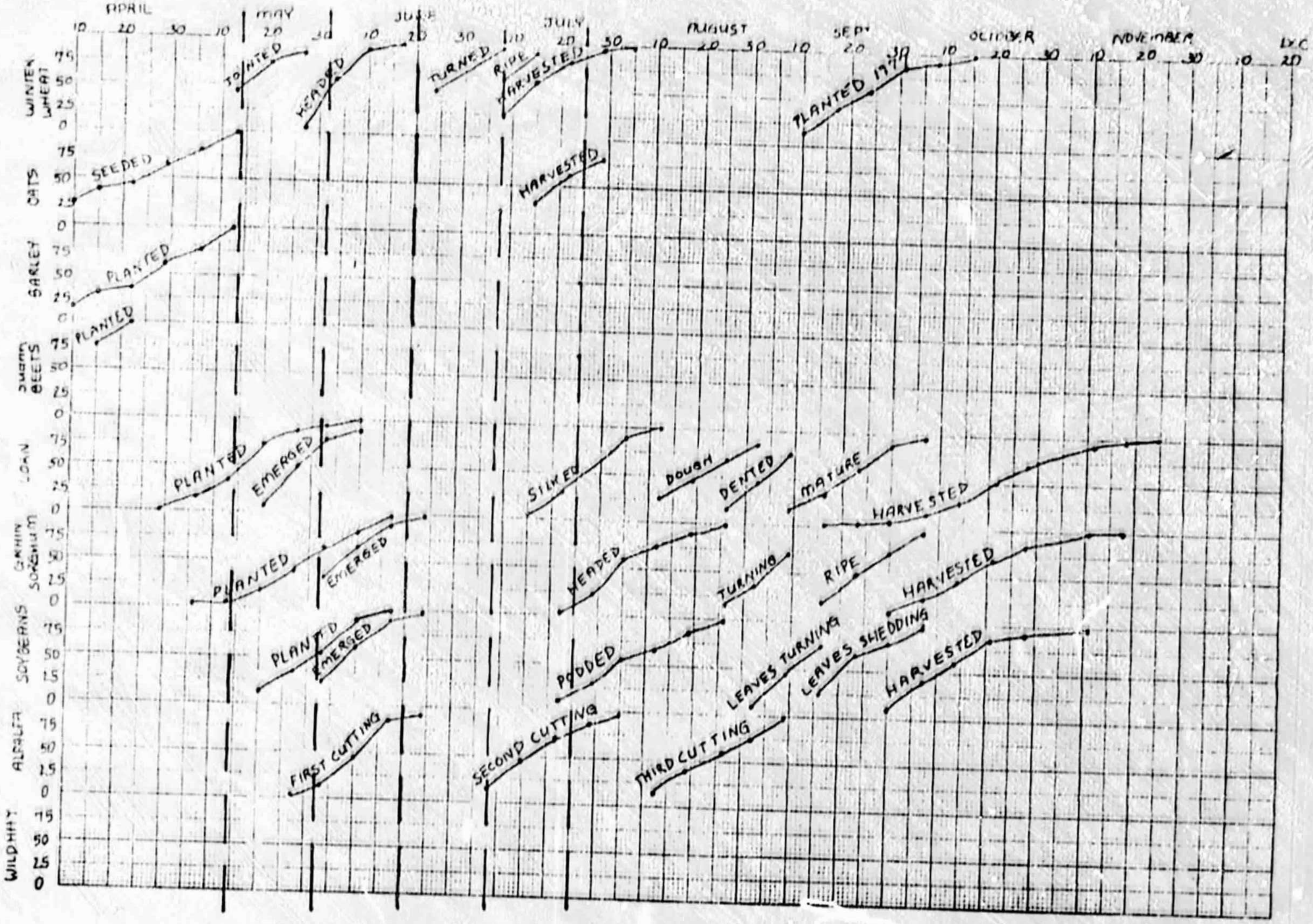

Figure 2.17
Nebraska 1978 Crop Calendar
— — — = Landsat Pass Dates, for Segment 1572, Used for PxP DFS.

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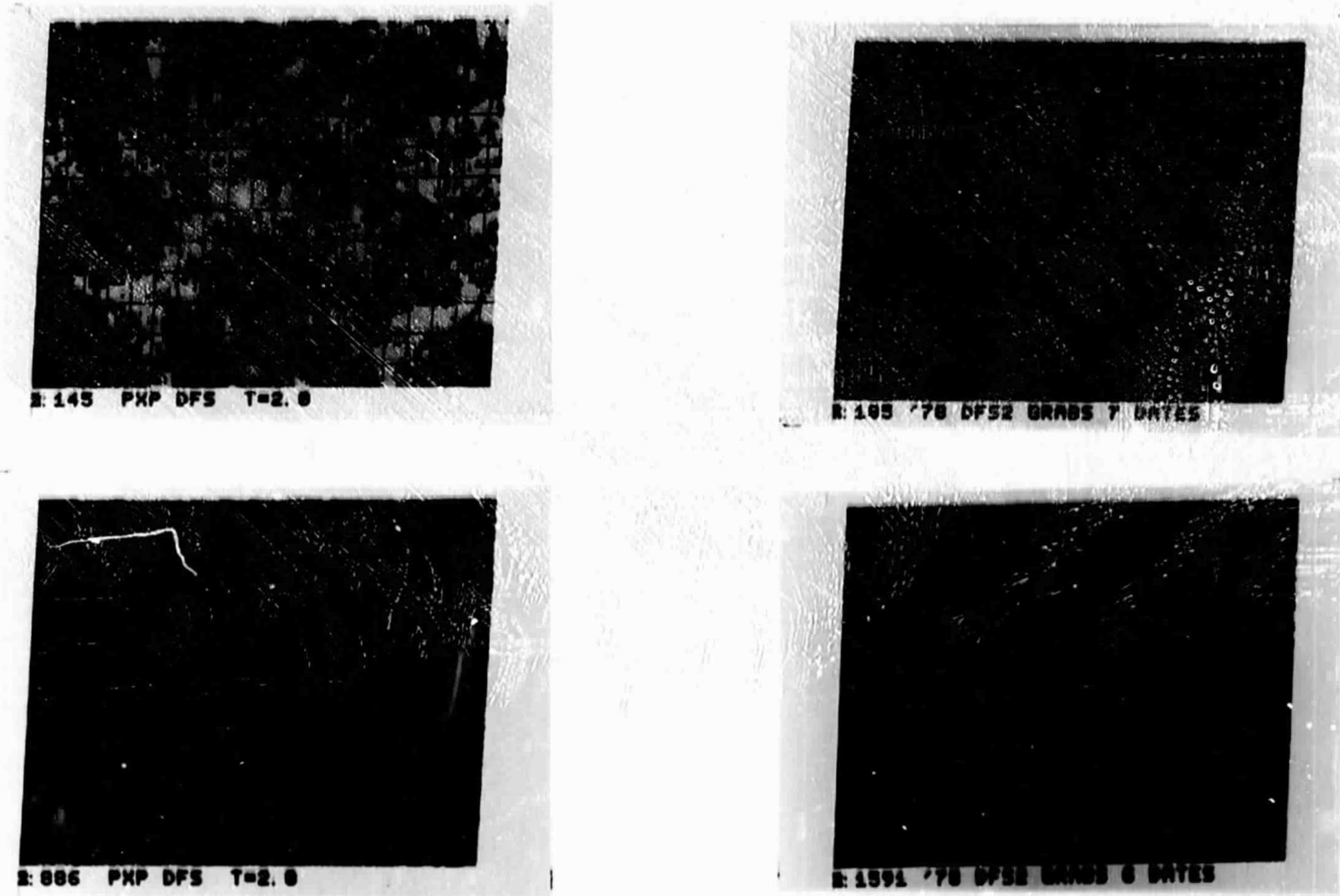


Figure 2.18

Four Corn-belt Segments
Pixel-by-Pixel Delta Function Stratification

red, yellow = summer crops
purples = small grain
green, cyan, blue = pasture/alfalfa/grass
black = fallow
grey = unclassified

2.5 SUBTASK C: ADVANCED SPECTRAL AIDS AND PROCEDURES FOR MULTICROP

2.5.1 SPECIFIC OBJECTIVE

The specific objectives of Subtask C were 1.) to refine current spectral aids so that they were more specific to the crop types of interest, and 2.) to develop a data analysis procedure that would allow the analyst to efficiently and effectively process the increased amount of detailed temporal-spectral data required for differentiation between closely related crop types.

2.5.2 APPROACH

Refined Spectral Aids

The spectral aids which were refined within this subtask were the spectral scatter plots. The scatter plots currently being employed take a 9% sample of the spectral data from all classes throughout the entire segment for each acquisition. These scatter plots normally display the Tassel Cap Greenness (TC-2) versus the Tassel Cap Brightness (TC-1) of all of the 209 sample points. For segments which contain substantial proportions of several crop groups/land use classes (summer crops, small grains, urban, fallow, pasture, etc.) the resultant scatter plot is composed of overlapping spectral distributions from all crop groups/land use classes present. If the desire is to separate specific crop types within a broader crop group class, then it would be more efficient to display only the spectral distributions within the specific crop group for which specific crop type labeling is required. Thus the relationships between the specific crop types within the group of interest could be more effectively analysed. In order to sample the spectral distribution from within only one crop group, it is first necessary to stratify a segment into crop group strata. After a segment has been stratified into crop group strata, then sampling of the different crop type specific spectral distributions within the crop group stratum can be relatively simple.

The pixel-by-pixel Delta Function Stratification Procedure (PxP-DFS; see Section 2.4) was used to produce the crop group stratification. The crop groups/land use strata that were determined are 1.) Small Grains, 2.) Summer Crops, 3.) Fallow and Urban, (Central Business District), 4.) Pasture, Alfalfa, Range, Riparian, and Urban, (Residential), 5.) Alfalfa, and 6.) misregistered pixels. Scatter plots are then produced by sampling only within the temporal pattern (see Section 2.4) classes belonging to the crop group stratum of interest. Such crop group specified scatter plots have been named stratified scatter plots.

When PxP-DFS is used to produce stratified scatter plots, a slight modification in the DFS procedure is made so that only relatively pure temporal pattern classes (TPC) within a crop group stratum are sampled. This is done to minimize the sampling of misregistered pixels. Thus only the "pure temporal pattern classes" plus the A subclasses within a crop group stratum and not the B or insignificant (<50 pixels) temporal pattern classes (see Section 2.4) are sampled for the stratified scatter plots.

Another refinement in the stratified scatter plots was a change in the rate of sampling of the spectral data. Instead of sampling only the 209 grid points that fell within the crop group stratum of interest, the sample was increased to the 897 (5 pixel by 5 pixel) grid points within a crop group stratum. This new sampling rate will tend to provide a minimum of 30 sample pixels from any major crop type (>5% of segment) even allowing for 20% loss of pixels to the B or insignificant temporal pattern classes.

A third refinement to the scatter plots and other spectral aids employing Tassel Cap Greenness, was the substitution of GRABS for Greenness. GRABS stands for Greenness Above Bare Soil, and is produced by subtracting the projection onto the Tassel Cap Greenness-Brightness Plane of the 7/5VI "soil line" (2xMSS7/MSS5 = 1.10) from the Tassel Cap Greenness Value. Thus a GRABS value of 0 can be considered by the analyst as the threshold for detectable green vegetation.

Another type of scatter plot examined within this subtask was the stratified multitemporal scatter plot. In the multitemporal scatter plot the GRABS bands from two different dates are plotted against each other. The two dates that are usually paired are 1.) Acquisition N vs. Acquisition N + 1, or 2.) Acquisition N vs. Acquisition N + 2. Again the higher sampling rate is utilized. An example of unitemporal and multitemporal stratified scatter plots versus currently employed unstratified scatter plot appears in Figure 2.19 and 2.20.

Development of an Efficient, Standardized Analysis Procedure

The philosophy underlying the development of a refined standardized analysis procedure was that 1.) the procedure should be comfortable for the AI to utilize, that is, the procedure should be logically compatible with the AI's standard analysis process; 2.) the procedure should minimize tedious data handling by the AI. By minimizing tedious tasks, errors that result from analyst fatigue, frustration and boredom can be reduced; and 3.) the procedure should effectively utilize the unique capability of the AI to evaluate and make decisions about abnormal or variant situations.

A standard image interpretation procedure is that of starting with a general level of analysis for contextual understanding, and then proceeding as necessary to ever increasing levels of detailed analysis. This system of working from the general to the specific provides the framework for the data analysis procedure being developed within this subtask. To minimize tedious data handling or repetitive data analysis by the analyst, machine processing is utilized at any analysis level where the analyst can specify a given decision rule as appropriate for all pixels at that level of analysis. In situations

where a given decision rule can not be specified, then the analyst is to analyze each pixel.

Multicrop Analysis Procedure

The procedure is as follows:

First General Level - Crop Group Stratification

At a 1st general level of analysis the segment is stratified into crop group strata. The stratification is based mainly on temporal pattern characteristics. The method of stratification is the pixel-by-pixel Delta Function Stratification Procedure (PxP-DFS) described in Section 2.4 (Subtask B). The output from the 1st analysis level is a crop group stratification consisting of from 2 to 6 strata. This stratification could be viewed as comparable to the P-1 stratification except that with DFS there are usually more than two strata, P-1 having had only two possible strata (i.e. small grains, and non-small grains).

Second Level - Crop Type Stratification

At the second level of analysis, the segment is stratified into crop type strata (e.g. corn, soybeans, sunflowers, etc.) This second stratification is mainly based on observed spectral differences and subtle temporal differences among the various spectral distributions within a given crop group stratum. Thus each crop group stratum is processed separately at the second and all succeeding levels of analysis.

The crop type stratification results from the application of linear discriminants to selected features (e.g. GRABS bands, and brightness bands for selected acquisitions). The linear discriminants are specified by the analyst after he reviews the first level DFS stratification, the stratified scatter plots, the Landsat image products, and other pertinent ancillary data (i.e. crop calendars, historical agricultural statistics, etc.).

In order to place the linear discriminants in the Tassel Cap transformed multitemporal data, the analyst examines the stratified unitemporal and multitemporal scatter plots. Then based on available labeling guidelines which describe the temporal-spectral characteristics of the various possible crop types, the analyst chooses those scatter plots which seem to best show spectral-temporal separation between the crop types present.

The analyst sets his initial expectations about which crop types are present within a segment from historical agricultural statistics, and the DFS stratification. Note that these expectations are only

first working hypotheses. The analyst must be prepared to adjust these initial expectations as the analysis continues and data which is contrary to his expectations is encountered. Thus if in a given area sunflowers are not reported to occur or be present in significant amounts in the historical statistics, the initial expectation would be that sunflowers are not a likely crop type to be present. However, if a spectral distribution is observed within the stratified scatter plots which is "typical" of sunflowers according to established guidelines, then the analyst should adjust his expectations to include the possibility of sunflowers being present.

After the analyst specifies the linear discriminants and the appropriate spectral features, the machine assigns each pixel to its appropriate crop type stratum. A hard copy image is then made of this crop type stratification so that the spacial distribution of the crop type strata can be analysed. Figure 2.21 and 2.22 show the crop type strata resultant from the second level of analysis for two segments that were part of the interpretation test described in Section 2.3 (Subtask A).

The value to the analyst of the crop type strata image product is that a quick check can be made by evaluation of the spacial integrity of the crop type strata, of the effectiveness of the linear discriminants in separating the crop types. In addition, in proceeding to the third level of analysis the analyst can easily determine the relevance of the spectral data for a particular sample pixel relative to the "pure" spectral data from the field center with which the pixel is associated. For example in Figure 2.21B sample pixel line 80, point 30 appears to be sunflowers based on its actual spectral values, however it can be seen that pixel 80, 30 falls in a boundary or fringe area of a field which is south (below) of pixel 80,30. The field center spectrally looks like corn and is probably the more accurate spectral data to use to label pixel 80, 30.

When selecting spectral features and/or acquisitions in which to place crop type linear discriminants, the analyst should try to select some spectral features or acquisitions which are partially redundant. That is, if two crops are fairly well discriminated on one acquisition but a certain amount of overlap exists between their spectral distributions, a second acquisition which also allows fair discrimination between the two crop types should be chosen as a double check on separating the crop types. Thus, if the linear discriminant(s) from both acquisitions call a pixel-corn, the analyst can feel more confident that the given pixel is spectrally consistent with corn spectra. However, if the linear discriminant(s) place the

pixel in a corn spectral class on one acquisition, and in a soybean spectral class on another acquisition, then the analyst is aware of the conflicting spectral evidence and must look to additional data products before placing the final crop type label on the pixel. At this point the analyst has now started level three analysis.

Third Level - Final Crop Type Labeling of Sample Pixels

At the third level of analysis, a final crop type label is assigned to each specific sample pixel. The labeled pixels from this third level are used similarly to the way Type 2 dots for P-1 were used to produce the final segment estimate. While in this discussion of level three analysis, the labeling target is taken to be an individual sample pixel, this analysis procedure could be applied just as easily with no significant modifications to other types of labeling targets such as field centers or BLOBS. Also, the analysis procedures and applied decision logic for level one and two processing are not directly dependent upon the type of labeling targets such as pixels, field centers, BLOBS or clusters. The above described three-level analysis procedure is diagramed in Figure 2,23.

2.5.3 CONCLUSION AND RECOMMENDATIONS

The above described data analysis flow provides an overall structure within which to develop standardized objective labeling and area estimation procedures. The next step is to document specific analysis procedural steps and decision logic to be applied at each level (1st-crop group stratification, 2nd-crop type stratification, and 3rd-crop type label for each selected labeling target). The stratification produced at levels 1 and 2 of the analysis procedure can be useful in two ways. One - in producing aids for the analyst for tertiary level labeling, and two - in providing additional physically based stratification of the spectral data that can be effectively incorporated into the overall area estimation procedure.

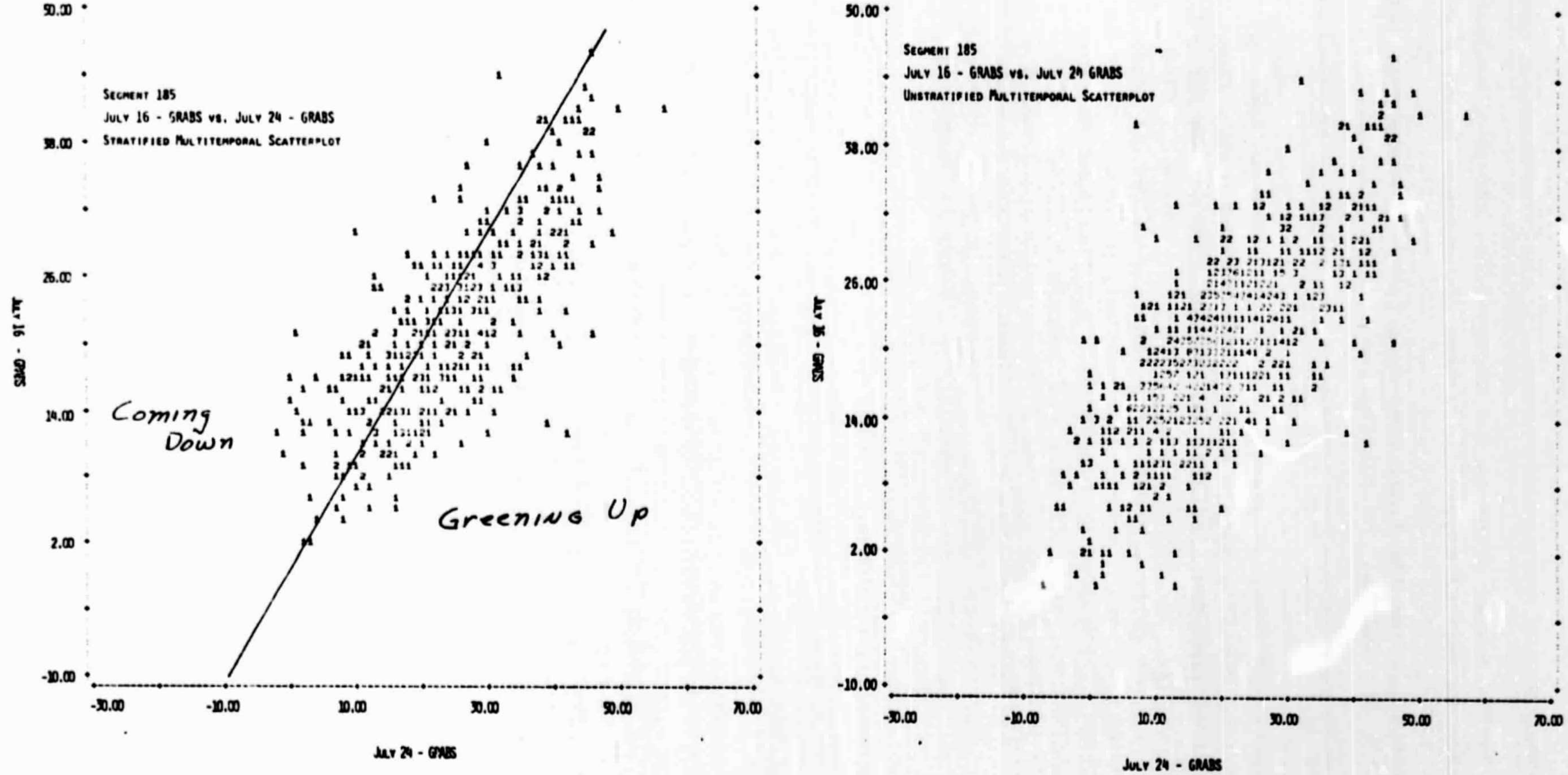
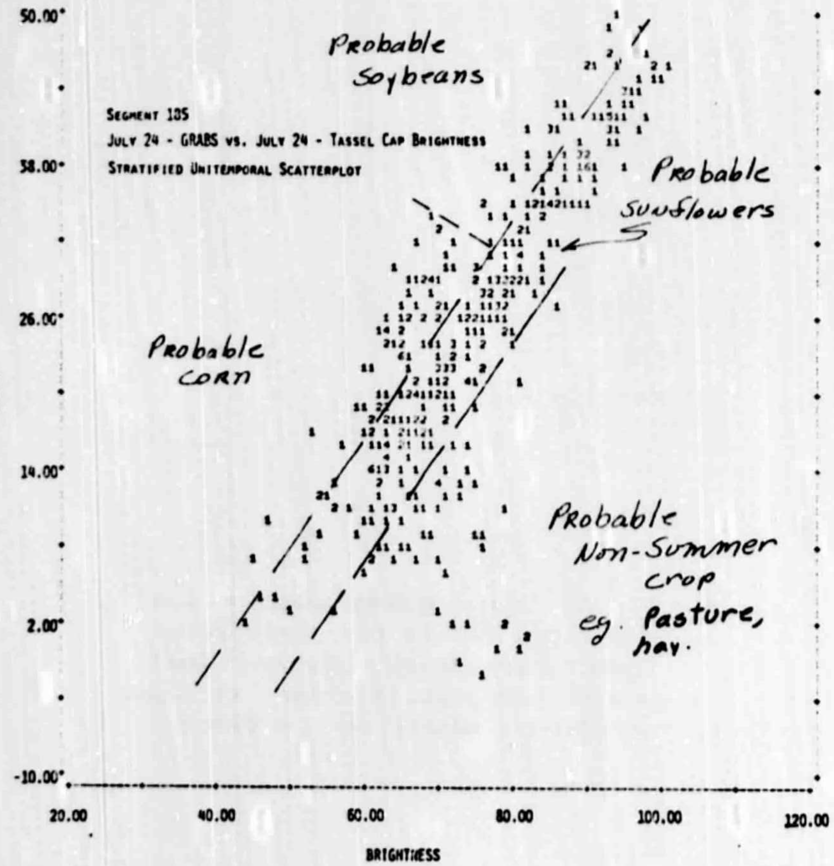


Figure 2.19

The startifed summer crops scatter plot on the left indicates that prior to 24 July most of the summer crops were still not at their peak GRABS values (Greenness - vegetation threshold). This is indicated by the majority of pixels still within the area labeled greening up on the lower side of the 1.1 line in the plot. This type of data allows the analyst to evaluate when peak greenness occurs and the variation is peaking dates among the summer crops.



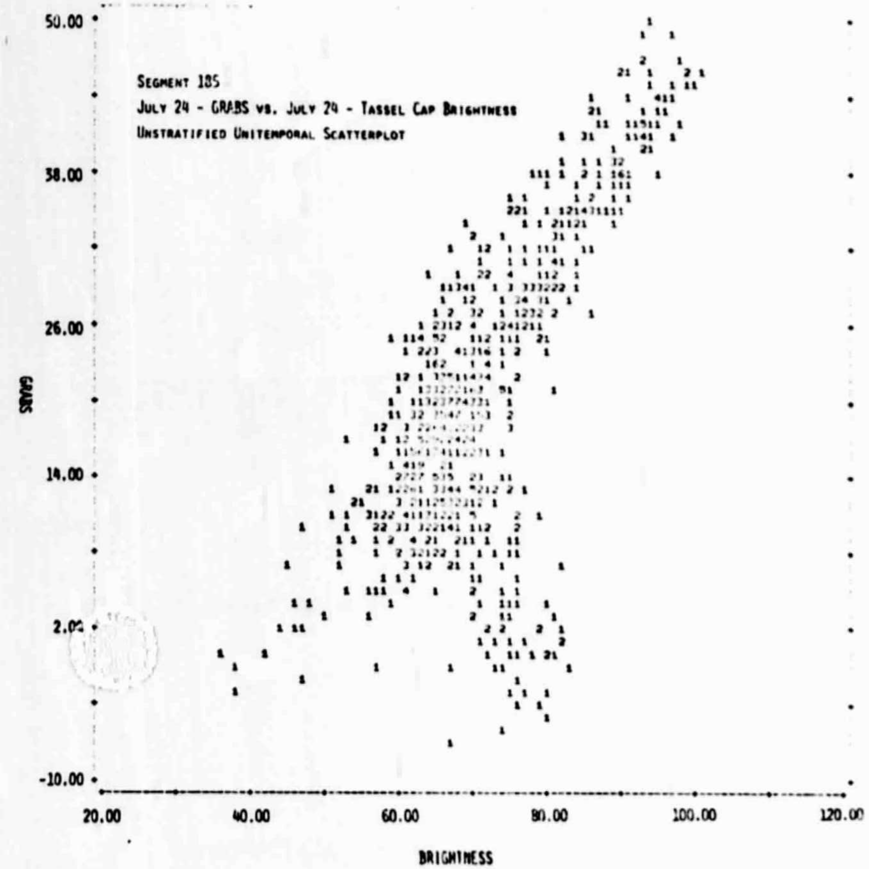


Figure 2.20

By eliminating pixels from the scatter plots which have a very low probability of being summer crops, the different spectral groupings within the summer crops can be more clearly discerned and more confident decision boundaries can be placed in the data by the analyst.

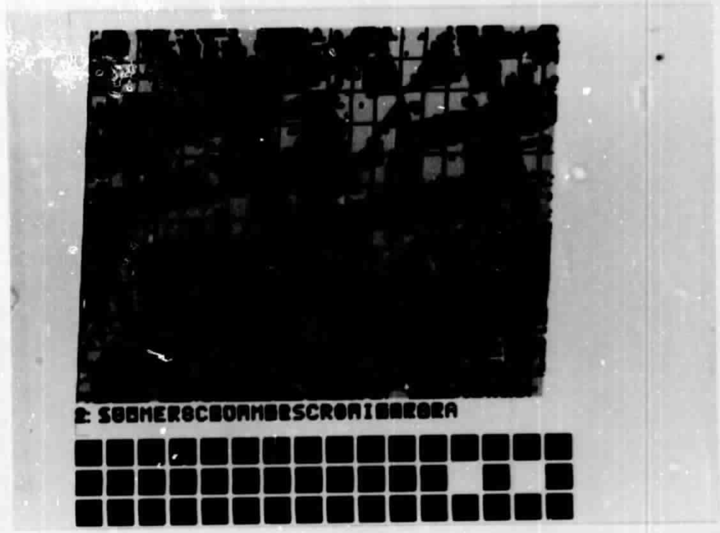


Figure 2.21

A. *Second level crop type linear discriminants applied to segment 185.*

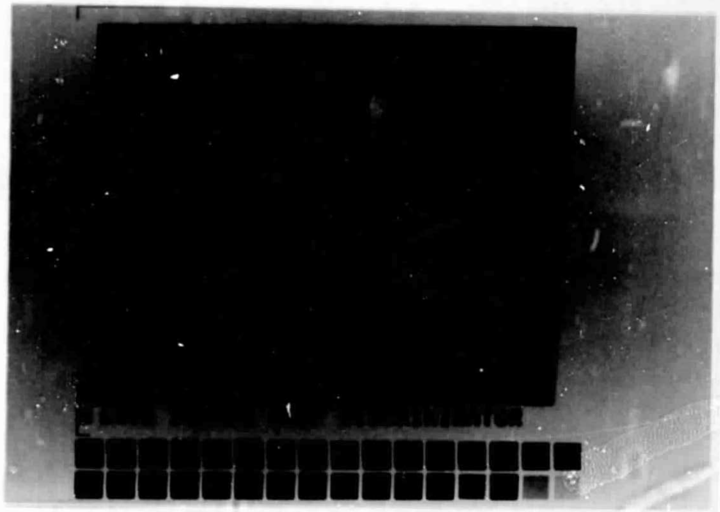
B. *Second level summer crop strata displayed within the first level summer crop group stratum. Small grains and pasture-urban 1st level strata are masked out in black.*

COLOR KEY: *yellow = Potential Sunflowers;*

green = Potential Soybeans

brown = Potential corn

blue = Potential sugar beets.



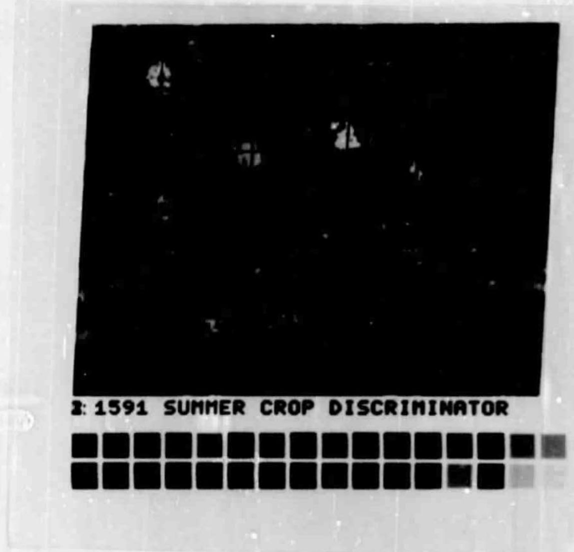


Figure 2.22

A. *Second level crop type linear descriminants applied to segment 1591.*

B. ***Second level summer crop type strata displayed within the first level summer crop group. Small grains and pasture-urban 1st level strata are masked out in black. Discrimination of crop type in segment 1591 was not as good as in segment 185, Figure 2.21, because of spectral/temporal similarity of corn and sorghum.***

COLOR KEY: Blue/red - violet = Potential Sorghum;

Red/orange = Portential corn;

Yellow/blue = Potential soybean.

LEVEL ONE PROCESSING: CROP GROUP STRATIFICATION (PIXEL-BY-PIXEL DFS)

MACHINE →	ANALYST →	MACHINE →	ANALYST
DATA REGISTERED, NORMALIZED, TRANSFORMED PFC'S PRODUCED CCT'S PRODUCED	SPECIFICATION OF ACQ. FOR TEMPORAL CLASS PROCESSING BY MACHINE	ASSIGNMENT OF EACH PIXEL TO A - TEMPORAL CLASS	ASSIGNMENT OF TEMPORAL CLASSES TO A MAJOR CROP GROUP STRATUM

↓

LEVEL TWO PROCESSING: CROP TYPE STRATIFICATION WITHIN A CROP GROUP STRATUM

ANALYST →	MACHINE →	ANALYST →	MACHINE
SPECIFICATION OF TEMP. CLASSES USED FOR STRATIFIED SPECTRAL AIDS	PRODUCTION OF STRATIFIED SPECTRAL AIDS	SPECIFICATION OF DISCRIMINANTS & AND FEATURES FOR OPTIMUM CROP TYPE STRATIFICATION	ASSIGNMENT OF PIXELS TO CROP TYPE STRATA ACCORDING TO SPECIFIED DECISION RULES.

↓

LEVEL THREE PROCESSING: FINAL CROP TYPE LABELING OF SAMPLE UNITS - E.G. PIXELS, BLOBS, ETC.

ANALYST

ASSIGNMENT OF FINAL CROP TYPE LABEL TO EACH SAMPLE UNIT

Figure 2.23

Three level multicrop analysis procedure

References

1. Hay, C.M. and R.W. Thomas, 1977. Development of Techniques for Producing Static Strata Maps and Development of Photointerpretation Methods Based on Multitemporal Landsat Data. Final report for NASA contract NAS9-14565. Principal investigator: R.N. Colwell. University of California, Space Sciences Laboratory, Series 19, Issue 1, Berkeley, December.

Appendix A

Interpretation test results by individual analyst and by segment combined across analysts. The crop codes are defined in Table 2.4. Fractional values represent mixed pixels.

Segment 145

Analyst B

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	50.0	7.5		1.0	1.0		59.5	9.5
SY	1.0	32.5		3.0			36.5	4.0
SG			0				0	0
APR	2.0			56.0		7.5	65.5	9.5
I					0	3.0	3.0	3.0
NA				1.0		6.5	7.5	1.0
Total	53.0	40.0	0	61.0	1.0	17.0	172.0	
Omission	3.0	7.5	0	5.0	1.0	10.5		27.0

Segment 145

Analyst C

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	50.0	1.0		1.0			52.0	2.0
SY		28.5					28.5	0
SG			0				0	0
APR		1.0		66.0		6.0	73.0	7.0
I					0		0	0
NA					1.0	17.5	18.5	1.0
Total	50.0	30.5	0	67.0	1.0	23.5	172.0	
Omission	0	2.0	0	1.0	1.0	6.0		10.0

Segment 145

Analyst E

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	54.83	2.0		2.5	1.0	1.33	61.67	6.83
SY	1.0	30.83		1.0			32.83	2.0
SG			0	3.0			3.0	3.0
APR		3.33		43.5		5.0	51.83	8.33
I				1.0	0	1.0	2.0	2.0
NA				1.83		18.33	20.67	1.83
Total	55.83	36.17	0	52.83	1.0	26.17	172.0	
Omission	1.0	5.33	0	9.33	1.0	7.33		24.0

Segment 145

Analyst COMBINED

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	154.83	10.5		4.5	2.0	1.33	173.17	18.33
SY	2.0	91.83		4.0			97.83	6.0
SG			0	3.0			3.0	3.0
APR	2.0	4.33		165.5		18.5	190.33	24.83
I				1.0	0	4.0	5.0	5.0
NA				2.83	1.0	42.83	46.67	3.83
Total	158.83	106.67	0	180.83	3.0	66.67	516.0	
Omission	4.0	14.83	0	15.33	3.0	23.83		61.0

Segment 185

Analyst A

Ground Data

Analyst	C	SY	SU	SB	Other SC	SG	APR	I	NA	Total	Commission
C	6.5	.5	1.0							8.0	1.5
SY		10.5		1.0						11.5	1.0
SU	1.0	2.5	35.5	1.0						40.0	4.5
SB				0						0	0
Other SC					0					0	0
SG						88.0	3.5	1.0		92.5	4.5
APR							7.5	1.0		8.5	1.0
I		1.0						1.0		2.0	1.0
NA		2.0							21.5	23.5	2.0
Total	7.5	16.5	36.5	2.0	0	88.0	11.0	3.0	21.5	186.0	
Omission	1.0	6.0	1.0	2.0	0	0	3.5	2.0	0		15.5

Segment 185

Analyst C

Ground Data

Analyst	C	SY	SU	SB	Other SC	SG	APR	I	NA	Total	Commission
C	7.0	1.5	8.5							17.0	10.0
SY		12.0		1.5						13.5	1.5
SU	.5	3.0	28.0	1.5						33.0	5.0
SB				0						0	0
Other SC								.5		.5	.5
SG						87.0	2.0	1.0		90.0	3.0
APR						2.0	11.0	1.0		14.0	3.0
I								.5		.5	0
NA							1.0		16.5	17.5	1.0
Total	7.5	16.5	36.5	3.0	0	89.0	14.0	3.0	16.5	186.0	
Omission	.5	4.5	8.5	3.0	0	2.0	3.0	2.5	0		24.0

Segment 185

Analyst D

Ground Data

Analyst	C	SY	SU	SB	Other SC	SG	APR	I	NA	Total	Commission
C	4.0	4.0	10.0							18.0	14.0
SY	2.0	3.5	5.0	.5						11.0	7.5
SU		7.5	14.5							22.0	7.5
SB				2.0						3.0	1.0
Other SC					0					0	0
SG						87.5	3.0	1.5		92.0	4.5
APR	1.0		.5			1.5	9.5	1.0		13.5	4.0
I								1.0	.5	1.5	.5
NA			.5						24.5	25.0	.5
Total	7.0	15.0	31.5	2.5	0	89.0	12.5	3.5	25.0	186.0	
Omission	3.0	11.5	17.0	.5	0	1.5	3.0	2.5	.5		39.5

Segment 185

Analyst COMBINED

Ground Data

Analyst	C	SY	SU	SB	Other SC	SG	APR	I	NA	Total	Commission
C	17.5	6.0	19.5							43.0	25.5
SY	2.0	26.0	5.0	3.0						36.0	10.0
SU	1.5	13.0	78.0	2.5						95.0	17.0
SB			1.0	2.0						3.0	1.0
Other SC					0			.5		.5	.5
SG						262.5	8.5	3.5		274.5	12.0
APR	1.0		.5			3.5	28.0	3.0		36.0	8.0
I		1.0						2.5	.5	4.0	1.5
NA		2.0	.5				1.0		62.5	66.0	3.5
Total	22.0	48.0	104.5	7.5	0	266.0	37.5	9.5	63.0	558.0	
Omission	4.5	22.0	26.5	5.5	0	3.5	9.5	7.0	.5		79.0

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Segment 241

Analyst A

Ground Data

Analyst	C	SY	SU	SR	SG	APR	I	NA	Total	Commission
C	46.83	7.0	1.0	1.0	1.0	1.0			57.83	11.0
SY		3.0							3.0	0
SU			0						0	0
SR				0					0	0
SG	1.0				41.83	5.5	2.5		50.83	9.0
APR			1.0		6.0	54.5	2.0		63.5	9.0
I		1.0			1.0	2.5	3.0		7.5	4.5
NA						0	0	12.33	12.33	0
Total	47.83	11.00	2.0	1.0	49.83	63.5	7.5	12.33	195.0	
Omission	1.0	8.0	2.0	1.0	8.0	9.0	4.5	0		33.5

Segment 241

Analyst C

Ground Data

Analyst	C	SY	SU	SR	SG	APR	I	NA	Total	Commission
C	42.83	1.0	3.0	1.0		.5	1.0		49.33	6.5
SY	5.33	7.83		1.0		2.0			16.17	8.33
SU			1.0						1.0	0
SR				0					0	0
SG					33.33			1.0	34.33	1.0
APR					14.0	63.83	9.5		87.33	23.5
I							0		0	0
NA						1.0		5.33	6.33	1.0
Total	48.17	8.83	4.0	2.0	47.33	67.33	10.5	6.33	195.0	
Omission	5.33	1.0	3.0	2.0	14.0	3.5	10.5	1.0		40.33

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Segment 241

Analyst F

Ground Data

Analyst	C	SY	SU	SR	SG	APR	I	NA	Total	Commission
C	48.5	9.5	3.0	1.0	4.0	7.5		1.0	74.5	26.0
SY		0					1.0		1.0	1.0
SU			0						0	0
SR				0					0	0
SG	1.0				40.0	7.0	1.0		49.0	9.0
APR	1.0	1.0			10.0	43.5	1.0	1.0	57.5	14.0
I	1.0	1.0					4.0	1.0	7.0	3.0
NA								6.0	6.0	0
Total	51.5	11.5	3.0	1.0	54.0	58.0	7.0	9.0	195.0	
Omission	3.0	11.5	3.0	1.0	14.0	14.5	3.0	3.0		53.0

Segment 241

Analyst G

Ground Data

Analyst	C	SY	SU	SR	SG	APR	I	NA	Total	Commission
C	35.0	3.5	1.0	1.5		1.0		.5	42.5	7.5
SY	7.0	6.0	1.0		4.5		1.0		19.5	13.5
SU			0						0	0
SR				0					0	0
SG	.5	1.0			41.83	2.0	.5	1.0	46.83	5.0
APR	3.33	.5			3.5	58.0	4.5		70.33	12.33
I					.5	1.0	1.0		2.5	1.5
NA						1.0	.5	11.83	13.33	1.5
Total	46.33	11.0	2.0	1.5	50.33	63.0	7.5	13.33	195.0	
Omission	11.33	5.0	2.0	1.5	8.5	5.0	6.5	1.5		41.33

Segment 241

Analyst COMBINED

Ground Data

Analyst	C	SY	SU	SR	SG	APR	I	NA	Total	Commission
C	173.17	21.0	8.0	4.5	5.0	10.0	1.0	1.5	224.17	51.0
SY	12.33	16.83	1.0	1.0	4.5	2.0	2.0		39.67	22.83
SU			1.0						1.0	0
SR				0					0	0
SG	2.5	1.0			157.0	14.5	4.0	2.0	181.0	24.0
APR	4.83	1.5	1.0		33.5	219.83	17.0	1.0	278.67	58.83
I	1.0	2.0			1.5	3.5	8.0	1.0	17.0	9.0
NA						2.0	.5	36.0	38.5	2.5
Total	193.83	42.33	11.0	5.5	201.5	251.83	32.5	41.5	780.0	
Omission	20.67	25.5	10.0	5.5	44.5	32.0	24.5	5.5		168.17

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Segment 324

Analyst B

Ground Data

Analyst	C	SY	SR	SG	APR	I	NA	SG, APR'	Total	Commission
C	79.0	7.0	1.0						37.0	8.0
SY	6.0	79.0							35.0	6.0
SR			0						0	0
SG				0					0	0
APR	4.0	.5			6.5		1.0	2.0	14.0	7.5
I	.5			1.0		0	.5		2.0	2.0
NA							17.0		17.0	0
SG, APR'								0	0	0
Total	39.5	36.5	1.0	1.0	6.5	0	13.5	2.0	205.0	
Omission	10.5	7.5	1.0	1.0	0	0	1.5	2.0		23.5

'Double Cropped

Segment 324

Analyst F

Ground Data

Analyst	C	SY	SR	SG	APR	I	NA	SG, APR'	Total	Commission
C	87.5	10.5	1.0						99.5	11.5
SY	2.5	33.0							85.5	2.5
SR			0						0	0
SG		1.0		0					1.0	1.0
APR					6.0			1.0	7.0	1.0
I	1.0			1.0		0	1.0	.5	3.5	3.5
NA							9.0		9.0	0
SG, APR'								0	0	0
Total	91.0	94.5	1.0	1.0	6.0	0	10.0	1.5	205.0	
Omission	3.5	11.5	1.0	1.0	0	0	1.0	1.5		19.5

'Double Cropped

Segment 324

Analyst D

Ground Data

Analyst	C	SY	SR	SG	APR	I	NA	SG, APR'	Total	Commission
C	66.5	4.0	1.0						71.5	5.0
SY	2.0	71.5							73.5	2.0
SR			0						0	0
SG				0					0	0
APR	6.5	5.0		.5	11.0			3.0	26.0	15.0
I						0			0	0
NA	2.5						31.5		34.0	2.5
SG, APR'								0	0	0
Total	77.5	80.5	1.0	.5	11.0	0	31.5	3.0	205.0	
Omission	11.0	9.0	1.0	.5	0	0	0	3.0		24.5

'Double Cropped

Segment 324

Analyst G

Ground Data

Analyst	C	SY	SR	SG	APR	I	NA	SG, APR'	Total	Commission
C	36.0	2.5							38.5	2.5
SY	.5	82.5						1.0	84.0	1.5
SR			0						0	0
SG				0					0	0
APR	1.0	.5			4.0				5.5	1.5
I						0	.5		.5	.5
NA		1.0	1.0	.5	.5		21.5	2.0	26.5	5.0
SG, APR'								0	0	0
Total	87.5	86.5	1.0	.5	4.5	0	22.0	3.0	205.0	
Omission	1.5	4.0	1.0	.5	.5	0	.5	3.0		11.0

'Double Cropped

Segment 324

Analyst COMBINED

Ground Data

Analyst	C	SY	SR	SG	APR	I	NA	SG, APR'	Total	Commission
C	319.0	24.0	3.0						346.0	27.0
SY	11.0	316.0						1.0	328.0	12.0
SR			0						0	0
SG		1.0		0					1.0	1.0
APR	11.5	6.0		.5	27.5		1.0	6.0	52.5	25.0
I	1.5			2.0		0	2.0	.5	6.0	6.0
NA	2.5	1.0	1.0	.5	.5		79.0	2.0	86.5	7.5
SG, APR'								0	0	0
Total	345.5	348.0	4.0	3.0	28.0	0	82.0	9.5	820.0	
Omission	26.5	32.0	4.0	3.0	.5	0	3.0	9.5		78.5

' Double Cropped

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Segment 854

Analyst C

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	98.33	6.33		1.5			106.17	7.83
SY	0	68.5					68.5	0
SG			2.0		.5		2.5	.5
APR		1.0	1.0	8.5	1.0		11.5	3.0
I					0		0	0
NA					.5	14.83	15.33	.5
Total	98.33	75.83	3.0	10.0	2.0	14.83	204.0	
Omission	0	7.33	1.0	1.5	2.0	0		11.83

Segment 854

Analyst E

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	103.17	3.5					106.67	3.5
SY		66.5					66.5	0
SG			2.0		.33		2.33	.33
APR	1.0	1.5	2.0	9.5		1.0	15.0	5.5
I		2.0			0	.5	2.5	2.5
NA		1.5			.50	9.0	11.0	2.0
Total	104.17	75.0	4.0	9.5	.83	10.5	204.0	
Omission	1.0	8.5	2.0	0	.33	1.5		13.83

Segment 854

Analyst F

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	94.33	13.0	.5	3.0		.5	111.33	17.0
SY	7.5	61.33					68.83	7.5
SG			0	1.0	.5		1.5	1.5
APR				2.0		1.0	3.0	1.0
I		1.0	1.5	.5	1.0		4.0	3.0
NA			1.0	1.0	.5	12.33	14.83	2.5
Total	102.33	75.33	3.0	7.5	2.0	13.83	204.0	
Omission	7.5	14.0	3.0	5.5	1.0	1.5		32.5

Segment 854

Analyst G

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	96.5	9.5					106.0	9.5
SY		66.0					66.0	0
SG		.5	1.0	1.0	1.0		3.5	2.5
APR	3.5	.5	2.5	8.5	1.5		16.5	8.0
I					0		0	0
NA						12.0	12.0	0
Total	100.0	76.5	3.5	9.5	2.5	12.0	204.0	
Omission	3.5	10.5	2.5	1.0	2.5	0		20.0

Segment 854

Analyst COMBINED

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	392.83	32.33	.5	4.5		.5	430.67	37.83
SY	7.5	262.33					269.83	7.5
SG		.5	5.0	2.0	2.33		9.83	4.83
APR	4.5	3.0	5.5	28.5	2.5	2.0	46.0	17.5
I		3.0	1.5	.5	1.0	.5	6.5	5.5
NA		1.5	1.0	1.0	1.5	48.17	53.17	5.0
Total	404.83	302.67	13.5	36.5	7.33	51.17	816.0	
Omission	12.0	40.33	8.5	3.0	6.33	3.0		78.17

Segment 883

Analyst D

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	53.0	5.0		5.0	.5		63.5	10.5
SY	4.0	50.5		1.0			55.5	5.0
SG			0				0	0
APR	3.0	5.5		29.0			37.5	8.5
I					0		0	0
NA						34.5	34.5	0
Total	60.0	61.0		35.0	.5	34.5	191.0	
Omission	7.0	10.5	0	6.0	.5	0		24.0

Segment 883

Analyst E

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	63.5	1.5		3.5			73.5	10.0
SY		51.0		1.0			52.0	1.0
SG			0	6.5			6.5	6.5
APR	1.5	5.0		9.5			16.0	6.5
I				1.0	1.0		2.0	1.0
NA				6.0	1.0	34.0	41.0	7.0
Total	65.0	57.5	0	32.5	2.0	34.0	191.0	
Omission	1.5	6.5	0	23.0	1.0	0		32.0

Segment 883

Analyst F

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	54.33	2.0		4.5			61.33	6.5
SY	6.0	63.33		6.0			75.33	12.0
SG			0	2.0			2.0	2.0
APR	1.0	3.0		13.0			22.0	4.0
I				1.0	1.0		2.0	1.0
NA				2.0	1.0	25.33	28.33	3.0
Total	61.83	68.33	0	33.5	2.0	25.33	191.00	
Omission	7.0	5.0	0	15.5	1.0	0		28.5

Segment 883

Analyst G

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	53.5	1.0		5.0	.5		60.0	6.5
SY	4.0	59.0		2.5	.5		66.0	7.0
SG			0				0	0
APR	1.5	5.0	.5	32.0		3.5	42.5	10.5
I					0		0	0
NA				.5	1.0	21.0	22.5	1.5
Total	59.0	65.0	.5	40.0	2.0	24.5	191.0	
Omission	5.5	6.0	.5	8.0	2.0	3.5		25.5

Segment 883

Analyst COMBINED

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	224.83	9.5		23.0	1.0		258.33	33.5
SY	14.0	223.83		10.5	.5		248.83	25.0
SG			0	8.5			8.5	8.5
APR	7.0	18.5	.5	88.5		3.5	118.0	29.5
I				2.0	2.0		4.0	2.0
NA				8.5	3.0	114.83	126.33	11.5
Total	245.83	251.83	.5	141.0	6.5	118.33	764.0	
Omission	21.0	28.0	.5	52.5	4.5	3.5		110.0

Segment 886

Analyst A

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	76.33		1.0	2.0			79.33	3.0
SY	1.5	43.33					44.83	1.5
SG			3.0	9.5		.5	13.0	10.0
APR	3.0	4.0	5.0	14.5	1.0		27.5	13.0
I				1.0	0	3.0	4.0	4.0
NA		.5		.5		34.33	35.33	1.0
Total	80.83	47.83	9.0	27.5	1.0	37.83	204.0	
Omission	4.5	4.5	6.0	13.0	1.0	3.5		32.5

Segment 886

Analyst B

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	89.0	2.0	.5			1.0	92.5	3.5
SY	6.5	43.0		.5			50.0	7.0
SG			0				0	0
APR	3.0	2.0	7.0	28.0		5.0	45.0	17.0
I			1.0	.5	0	3.0	4.5	4.5
NA		1.0				11.0	12.0	1.0
Total	98.5	48.0	8.5	29.0	0	20.0	204.0	
Omission	9.5	5.0	8.5	1.0	0	9.0		33.0

Segment 886

Analyst E

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	80.67			1.0			81.67	1.0
SY	2.83	47.83					50.67	2.83
SG			0	1.0	1.0		2.0	2.0
APR	1.5	2.0	7.0	26.0		1.5	38.0	12.0
I					1.0	3.0	4.0	3.0
NA	.5			.5		26.67	27.67	1.0
Total	85.5	49.83	7.0	28.5	2.0	31.17	204.0	
Omission	4.83	2.0	7.0	2.5	1.0	4.5		21.83

Segment 886

Analyst COMBINED

Ground Data

Analyst	C	SY	SG	APR	I	NA	Total	Commission
C	246.0	2.0	1.5	3.0		1.0	253.5	7.5
SY	10.83	134.17		.5			145.5	11.33
SG			3.0	10.5	1.0	.5	15.0	12.0
APR	7.5	8.0	19.0	68.5	1.0	6.5	110.5	42.0
I			1.0	1.5	1.0	9.0	12.5	11.5
NA	.5	1.5		1.0		72.0	75.0	3.0
Total	264.33	145.67	24.5	85.0	3.0	89.0	612.0	
Omission	13.33	11.5	21.5	16.5	2.0	17.0		87.33

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Segment 1075

Analyst A

Ground Data

Analyst	C	SR	SG	APR	I	NA	Total	Commission
C	54.0	1.0		2.5			57.5	3.5
SR	1.0	0					1.0	1.0
SG			2.5				2.5	0
APR	2.5		1.0	105.0	2.5		111.0	6.0
I		.5	.5	3.0	2.0		6.0	4.0
NA				2.5		24.5	27.0	2.5
Total	57.5	1.5	4.0	113.0	4.5	24.5	205.0	
Omission	3.5	1.5	1.5	8.0	2.5	0		17.0

Segment 1075

Analyst B

Ground Data

Analyst	C	SR	SG	APR	I	NA	Total	Commission
C	54.03	1.0		2.5	1.0		59.33	4.5
SR		0					0	0
SG			1.0	.5			1.5	.5
APR	2.0	.5	1.0	119.83	3.0	4.5	130.83	11.0
I				.5	1.83		2.33	.5
NA				1.5		9.5	11.00	1.5
Total	56.03	1.5	2.0	124.83	5.83	14.0	205.00	
Omission	2.0	1.5	1.0	5.0	4.0	4.5		18.0

Segment 1075

Analyst F

Ground Data

Analyst	C	SR	SG	APR	I	NA	Total	Commission
C	57.0	1.0		10.33	1.0	2.0	79.33	22.33
SR		0		1.0			1.0	1.0
SG			2.33	1.0			3.33	1.0
APR	2.5	.5	1.5	91.33	1.5		97.33	6.0
I				1.0	3.0		4.0	1.0
NA				2.0		18.00	20.00	2.0
Total	59.5	1.5	3.83	114.67	5.5	20.0	205.0	
Omission	2.5	1.5	1.5	23.33	2.5	2.0		33.33

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Segment 1075

Analyst COMBINED

Ground Data

Analyst	C	SR	SG	APR	I	NA	Total	Commission
C	165.83	3.0		23.33	2.0	2.0	196.17	30.33
SR	1.0	0		1.0			2.0	2.0
SG			5.83	1.5			7.33	1.5
APR	7.0	1.0	3.5	316.17	7.0	4.5	339.17	23.0
I		.5	.5	4.5	6.83		12.33	5.5
NA				6.0		52.0	58.0	6.0
Total	173.83	4.5	9.83	352.5	15.83	58.5	615.0	
Omission	8.0	4.5	4.0	36.33	9.0	6.5		68.33

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Segment 1572

Analyst A

Ground Data

Analyst	C	SR	SG	APR	I	NA	Total	Commission
C	18.0	1.5		1.0			20.5	2.5
SR	2.0	0					2.0	2.0
SG			3.0	1.0	1.0		5.0	2.0
APR	2.0		1.5	150.0	1.0	1.5	156.0	6.0
I					8.5	1.0	9.5	1.0
NA					2.0	4.0	6.0	2.0
Total	22.0	1.5	4.5	152.0	12.5	6.5	199.0	
Omission	4.0	1.5	1.5	2.0	4.0	2.5		15.5

Segment 1572

Analyst E

Ground Data

Analyst	C	SR	SG	APR	I	NA	Total	Commission
C	18.0	.5		1.0		1.0	20.5	2.5
SR		0					0	0
SG			0				0	0
APR	3.0	1.0	3.5	154.5	4.0	3.5	169.5	15.0
I					8.5		8.5	0
NA						.5	.5	0
Total	21.0	1.5	3.5	155.5	12.5	5.0	199.0	
Omission	3.0	1.5	3.5	1.0	4.0	4.5		17.5

Segment 1572

Analyst D

Ground Data

Analyst	C	SR	SG	APR	I	NA	Total	Commission
C	20.0	.5		2.0			22.5	2.5
SR	3.5	0					3.5	3.5
SG			1.5	3.0			4.5	3.0
APR		1.0	3.0	147.5	3.0	3.5	158.0	10.5
I				1.0	9.0	.5	10.5	1.5
NA						0	0	0
Total	23.5	1.5	4.5	153.5	12.0	4.0	199.0	
Omission	3.5	1.5	3.0	6.0	3.0	4.0		21.0

Segment 1572

Analyst G

Ground Data

Analyst	C	SR	SG	APR	I	NA	Total	Commission
C	24.5			1.0			25.5	1.0
SR		0					0	0
SG			1.5		1.0		2.5	1.0
APR	2.0	1.5	3.0	153.0	4.0	3.0	166.5	13.5
I					3.0		3.0	0
NA					1.0	.5	1.5	1.0
Total	26.5	1.5	4.5	154.0	9.0	3.5	199.0	
Omission	2.0	1.5	3.0	1.0	6.0	3.0		16.5

Segment 1572

Analyst COMBINED

Ground Data

Analyst	C	SR	SG	APR	I	NA	Total	Commission
C	80.5	2.5		5.0		1.0	89.0	8.5
SR	5.5	0					5.5	5.5
SG			6.0	4.0	2.0		12.0	6.0
APR	7.0	3.5	11.0	605.0	12.0	11.5	650.0	45.0
I				1.0	29.0	1.5	31.5	2.5
NA					3.0	5.0	8.0	3.0
Total	93.0	6.0	17.0	615.0	46.0	19.0	796.0	
Omission	12.5	6.0	11.0	10.0	17.0	14.0		70.5

Segment 1591

Analyst B

Ground Data

Analyst	C	SY	SB	SR	SG	APR	I	NA	Other Ag	Total	Commission
C	5.5	1.0					1.0			7.5	2.0
SY		0								0	0
SB			0							0	0
SR	22.0			2.0			.5	.5		25.0	23.0
SG					0					0	0
APR	1.0	1.0		3.0	5.0	115.5	9.5	15.5		150.5	35.0
I					1.0	1.0	1.0			3.0	2.0
NA							1.0	3.0		4.0	1.0
Other Ag									0	0	0
Total	23.5	2.0	0	5.0	6.0	116.5	13.0	19.0	0	190.0	
Omission	23.0	2.0	0	3.0	6.0	1.0	12.0	16.0	0		63.0

Segment 1591

Analyst C

Ground Data

Analyst	C	SY	SB	SR	SG	APR	I	NA	Other Ag	Total	Commission
C	14.0									14.0	0
SY	7.5	1.0		2.5			1.0			12.0	11.0
SB		1.0	0			1.0				2.0	2.0
SR	9.5			3.5				.33		13.33	10.33
SG					2.5	5.5	4.0	1.0		13.0	10.5
APR				1.0	1.0	97.33	3.5	7.0		109.33	12.5
I					1.5		8.0	1.0		10.5	2.5
NA					.33			14.0		14.33	.33
Other Ag					.5				0	.5	.5
Total	31.0	2.0	0	7.0	5.83	103.83	16.5	23.83	0	190.0	
Omission	17.0	1.0	0	3.5	3.33	6.5	8.5	9.33	0		49.67

Segment 1591

Analyst D

Ground Data

Analyst	C	SY	SB	SR	SG	APR	I	NA	Other Ag	Total	Commission
C	10.0	1.0		1.5		1.0	1.0			14.5	4.5
SY		0								0	0
SB			0							0	0
SR	12.33	1.0		3.0						16.83	13.83
SG					3.5	2.0	0			5.5	2.0
APR	5.0			2.0	3.0	106.33	6.5	19.5		142.33	36.0
I					1.0	2.5	5.5			9.0	3.5
NA	.5							1.33		1.83	.5
Other Ag									0	0	0
Total	28.33	2.0	0	6.5	7.5	111.83	13.0	20.83	0	190.0	
Omission	18.33	2.0	0	3.5	4.0	5.5	7.5	19.5	0		60.33

Segment 1591

Analyst COMBINED

Ground Data

Analyst	C	SY	SB	SR	SG	APR	I	NA	Other Ag.	Total	Commission
C	29.5	2.0		1.5		1.0	2.0			36.0	6.5
SY	7.5	1.0		2.5			1.0			12.0	11.0
SB		1.0	0			1.0				2.0	2.0
SR	44.33	1.0		8.5			.5	1.33		55.67	47.17
SG					6.0	7.5	4.0	1.0		18.5	12.5
APR	6.0	1.0		6.0	9.0	319.17	19.5	42.0		402.67	83.5
I					3.5	3.5	14.5	1.0		22.5	8.0
NA	.5				.33		1.0	18.33		20.17	1.83
Other Ag.					.5				0	.5	.5
Total	87.83	6.0	0	18.5	19.33	332.17	42.5	63.67	0	570.0	
Omission	58.33	5.0	0	10.0	13.33	13.0	28.0	45.33	0		173.0

Appendix B

Six variables of interest calculated by crop group (summer crops, small grains, alfalfa/pasture/range, idle and non-agriculture) and summer crop type (corn, soybeans, sunflowers, sugar beets and sorghum) from the test results presented in Appendix A. The six variables are defined in Table 2.5. "# Pixels" refers to the total number of sample pixels used to obtain the proportion estimates in each segment. "Combined" indicates segment results averaged across all analysts who labeled that segment.

TABLE B.1 INTERPRETATION TEST RESULTS: SUMMER CROPS

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct		% Commission (B)	
145	172	B*	54.07	1.74		97.85[1]	88.71[2]	5.20[1]	14.06[2]
		C*	46.80	0		98.76	97.52	1.24	2.48
		E*	53.49	1.45		96.38	93.11	6.17	9.34
		Combined	51.45	1.08	1.31	97.62	96.16	4.37	8.98
185	186	A*	33.60	-1.62		95.20	84.00	0	11.76
		C*	34.14	.27		100.00	74.02	.78	26.56
		D*	30.11	-1.08		96.43	42.86	0	55.56
		Combined	32.62	- .81	1.13	97.25	67.86	.28	30.14
241	195	A	31.71	- .52		95.15	80.59	3.29	18.08
		C	32.30	1.80		100.00	82.00	5.26	14.83
		F	34.36	4.36		92.54	72.39	17.88	35.76
		G*	31.19	.60		90.42	67.40	11.29	33.87
		Combined	32.39	1.56	2.39	94.52	75.59	9.82	27.88
824	205	B	86.34	-2.44		97.18	89.27	0	8.14
		D*	77.56	-6.83		91.19	86.79	0	4.83
		F	90.98	- .98		98.93	91.42	0	7.59
		G	85.37	-1.22		98.00	96.29	.57	2.32
		Combined	85.06	-2.86	3.71	96.48	91.04	.15	5.79
854	204	C	85.18	.24		99.42	95.79	.85	4.48
		E	87.83	-2.94		96.65	94.70	0	2.02
		F*	87.09	1.47		99.44	87.89	2.21	13.56
		G	86.52	-2.21		97.45	92.07	0	5.52
		Combined	86.70	- .85	1.98	98.23	92.60	.79	6.47
883	191	D	63.35	-1.05		92.97[1]	85.54[2]	5.46[1]	13.03[2]
		E	64.14	1.57		94.69	93.47	7.57	8.76
		F	68.15	3.40		96.92	90.78	7.68	13.53
		G*	64.92	1.05		94.76	90.73	6.74	10.71
		Combined	65.14	1.24	2.01	94.88	90.15	6.90	11.53
886	204	A	63.07	-2.20		94.17	93.00	2.42	4.78
		B	71.81	-1.96		95.90	90.10	1.40	7.37
		E	66.34	-1.47		97.04	94.92	.76	2.89
		Combined	67.08	-1.88	1.90	95.74	92.59	1.50	4.72
1075	205	A*	28.78	- .24		94.92	91.52	4.20	7.69
		B*	28.45	.49		95.71	94.00	5.80	7.58
		F*	29.76	9.42		95.08	93.44	27.80	29.04
		Combined	29.00	3.22	5.45	95.23	92.99	14.30	16.31
1572	199	A	11.81	- .50		91.49	76.60	4.44	20.00
		D	12.56	.51		96.00	80.00	7.69	23.08
		E*	11.31	-1.01		82.22	80.00	9.76	12.20
		G	14.07	-1.26		87.50	87.50	3.92	3.92
		Combined	12.44	- .57	.88	89.39	81.31	6.35	14.81
1591	190	B	18.68	-1.57		85.92	21.13	6.15	76.92
		C	21.05	.97		97.50	45.25	6.77	55.77
		D	19.38	-2.89		79.64	35.30	6.38	58.51
		Combined	19.71	-1.17	1.98	87.98	34.72	6.46	63.09

* First or second of five segments interpreted by analyst.

1 Crop group level - specific crop labels not considered.

2 Crop type level - specific crop labels used in calculations.

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TABLE B.2 INTERPRETATION TEST RESULTS: CORN

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	% Commission (B)
145	172	B*	30.81	3.78		94.34	7.98	15.97
		C*	29.07	1.16		100.00	1.64	3.85
		E*	32.46	3.39		98.21	5.88	11.07
		Combined	30.78	2.78	3.01	97.48	5.13	10.58
185	186	A*	4.03	.27		86.67	.84	18.75
		C*	4.03	5.11		93.33	5.60	58.82
		D*	3.76	5.92		57.14	7.82	77.78
		Combined	3.94	3.77	4.52	79.55	4.76	59.30
241	195	A	24.53	5.13		97.91	7.47	19.02
		C	24.70	.60		88.91	4.42	13.18
		F	26.41	11.80		94.17	18.12	34.90
		G*	23.76	-1.97		75.55	5.04	17.65
		Combined	24.85	3.89	6.52	89.34	8.70	22.75
824	205	B	43.66	-1.22		88.27	6.93	9.20
		D*	37.80	-2.92		85.80	3.92	6.99
		F	44.39	3.90		96.15	10.08	11.61
		G	42.68	.49		98.29	2.13	2.82
		Combined	42.13	.06	2.52	92.33	5.69	7.80
854	204	C	48.20	3.84		100.00	7.41	7.37
		E	51.06	1.23		99.04	3.51	3.28
		F*	50.16	4.66		92.67	16.72	15.20
		G	49.02	2.94		96.50	9.13	8.96
		Combined	49.61	3.17	3.41	97.04	9.20	8.78

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	% Commission (B)
883	172	D	31.41	1.84		88.33	8.02	16.54
		E	34.03	4.45		97.69	7.94	11.60
		F	32.37	-.26		88.67	5.03	10.60
		G*	30.89	.52		90.67	4.92	10.83
		Combined	32.18	1.63	2.43	91.46	6.47	12.97
886	204	A	39.62	-.73		94.43	2.43	3.78
		B	48.28	-2.94		90.36	3.32	3.78
		E	41.91	-1.88		94.35	.84	1.22
		Combined	43.27	-1.85	2.06	92.89	2.16	2.96
1075	205	A*	28.05	0		93.91	2.37	6.09
		B*	27.72	1.22		[illegible]	3.04	7.58
		F*	29.02	9.68		95.80	15.35	28.15
		Combined	28.26	3.64	5.63	95.40	6.87	15.46
1572	199	A	11.06	-.76		81.82	1.41	12.20
		D	11.81	-.50		85.11	1.42	11.11
		E*	10.55	-.25		85.71	1.40	12.20
		G	13.32	-.51		92.45	.58	3.92
		Combined	11.69	-.51	.54	86.56	1.21	9.55
1591	190	B	15.00	-11.05		19.30	1.24	26.67
		C	16.32	-8.95		45.16	0	0
		D	14.91	-7.28		35.29	2.78	31.03
		Combined	15.41	-9.09	9.22	33.59	1.35	18.06

* First or second of five segments interpreted by analyst.

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TABLE B.3 INTERPRETATION TEST RESULTS: SOYBEANS

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	% Commission (B)
145	172	B*	23.26	-2.04		81.25	3.03	10.96
		C*	17.73	-1.16		93.44	0	0
		E*	21.03	-1.94		85.24	1.47	6.09
		Combined	20.67	-1.71	1.76	86.09	1.47	6.13
185	186	A*	8.87	-2.69		63.64	.59	8.70
		C*	8.87	-1.61		72.73	.88	11.11
		D*	8.06	-2.15		23.33	4.39	68.18
		Combined	8.60	-2.15	2.19	54.17	1.96	27.78
241	195	A	5.64	-4.10		27.27	0	0
		C	4.53	3.76		88.67	4.47	51.52
		F	5.90	-5.39		0	.54	100.00
		G*	5.64	4.36		54.55	7.34	69.23
		Combined	5.43	- .34	4.44	39.76	3.09	57.55
824	205	B	42.20	- .74		91.32	5.06	7.06
		D*	39.27	-3.42		88.82	1.61	2.72
		F	46.10	-4.39		87.83	2.26	2.92
		G	42.20	-1.22		95.38	1.27	1.79
		Combined	42.44	-2.44	2.87	90.80	2.54	3.66
854	204	C	37.17	-3.59		90.33	0	0
		E	36.76	-4.16		88.66	0	0
		F*	36.93	-3.19		81.42	5.83	10.90
		G	37.50	-5.15		86.27	0	0
		Combined	37.09	-4.02	4.09	86.67	1.46	2.78
883	191	D	31.94	-2.88		82.79	3.85	9.00
		E	30.10	-2.87		88.70	.75	1.92
		F	35.77	3.67		92.08	9.78	15.93
		G*	34.03	.52		90.77	5.56	10.61
		Combined	32.96	- .39	2.75	88.88	4.88	10.05
886	204	A	23.45	-1.47		90.59	.96	3.35
		B	23.53	.98		89.58	4.48	14.00
		E	24.43	.41		95.99	1.84	5.59
		Combined	23.80	.03	1.05	92.11	2.43	7.79
1591	190	B	1.05	-1.05		0	0	0
		C	1.05	5.27		50.00	5.85	91.66
		D	1.05	-1.05		0	0	0
		Combined	1.05	1.06	3.16	16.66	1.95	91.66

* First or second of five segments interpreted by analyst.

TABLE B.4 INTERPRETATION TEST RESULTS: SUNFLOWERS

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	% Commission (B)
185	186	A*	19.62	1.89		97.26	3.01	11.25
		C*	19.62	-1.88		76.71	3.34	15.15
		D*	16.94	-5.11		46.03	4.85	34.09
		Combined	18.73	-1.70	3.33	74.64	3.75	17.89
241	195	A	1.03	-1.03		0	0	0
		C	2.05	-1.54		25.00	0	0
		F	1.54	-1.54		0	0	0
		G*	1.03	-1.03		0	0	0
		Combined	1.41	-1.28	1.31	9.09	0	0

* First or second of five segments interpreted by analyst.

TABLE B.5 INTERPRETATION TEST RESULTS: SUGAR BEETS

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	% Commission (B)
185	195	A*	1.08	-1.08		0	0	0
		C*	1.61	-1.61		0	0	0
		D*	1.34	.27		80.00	.54	33.33
		Combined	1.34	- .80	1.16	26.67	.18	33.33
1591	190	B	0	0		0	0	0
		C	0	1.05		0	1.05	100.00
		D	0	0		0	0	0
		Combined	0	.35	.61	0	.35	100.00

* First or second of five segments interpreted by analyst.

TABLE B.6 INTERPRETATION TEST RESULTS: SORGHUM

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	(B)
241	195	A	.51	- .51		0	0	0
		C	1.03	-1.03		0	0	0
		F	.51	- .51		0	0	0
		G*	.71	- .71		0	0	0
		Combined	.71	- .71	.72	0	0	0
824	205	B	.49	- .49		0	0	0
		D*	.49	- .49		0	0	0
		F	.49	- .49		0	0	0
		G	.49	- .49		0	0	0
		Combined	.49	- .49	.49	0	0	0
1075	205	A*	.73	- .24		0	.49	100.00
		B*	.73	- .73		0	0	0
		F*	.73	- .24		0	.49	100.00
		Combined	.73	- .40	.45	0	.33	100.00
1572	199	A	.75	.26		0	1.01	100.00
		D	.75	1.01		0	1.77	100.00
		E*	.75	- .75		0	0	0
		G	.75	- .75		0	0	0
		Combined	.75	- .06	.74	0	.69	100.00
1591	190	B	2.63	10.53		40.00	12.43	92.00
		C	3.68	7.28		50.00	5.64	74.69
		D	3.42	8.86		46.15	7.54	82.17
		Combined	3.25	6.52	8.99	45.96	8.55	84.73

* First or second of five segments interpreted by analyst.

TABLE B.7 INTERPRETATION TEST RESULTS: SMALL GRAINS

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	% Commission (B)
185	186	A*	47.31	2.42		100.00	4.59	4.86
		C*	47.85	.54		[illegible].75	3.09	3.33
		D*	47.85	1.61		98.31	4.64	4.89
		Combined	47.67	1.52	2.96	98.68	4.11	4.37
241	195	A	25.55	.52		83.95	6.20	17.71
		C	24.27	-6.67		70.42	.68	2.91
		F	27.69	-2.56		74.07	6.38	18.37
		G*	25.81	-1.79		83.11	3.56	10.68
		Combined	25.83	-2.62	3.69	77.92	4.15	13.26
824	205	B	.49	- .49		0	0	0
		D*	.24	- .24		0	0	0
		F	.49	0		0	.49	100.00
		G	.24	- .24		0	0	0
		Combined	.37	- .2[illegible]	.29	0	.12	100.00
854	204	C	1.47	- .24		66.66	.25	20.00
		E	1.96	- .82		50.00	.17	14.16
		F*	1.47	- .73		0	.75	100.00
		G	1.72	0		28.57	1.25	71.43
		Combined	1.65	- .46	.56	37.04	.60	49.14
883	191	D	0	0		0	0	0
		E	0	3.40		0	3.40	100.00
		F	0	1.05		0	1.05	100.00
		G*	.26	0		0	0	0
		Combined	.07	1.11	1.78	0	1.11	100.00
886	204	A	4.41	1.96		33.33	5.13	76.92
		B	4.17	0		0	0	0
		E	3.43	-2.45		0	1.02	100.00
		Combined	4.00	-1.55	2.56	12.24	2.04	80.00
1075	205	A*	1.95	- .73		62.50	0	0
		B*	4.17	-3.44		50.00	.25	33.33
		F*	1.87	1.62		60.84	.50	30.03
		Combined	1.60	1.19	1.94	59.31	.25	20.46
1572	199	A	2.26	.25		66.67	1.03	40.00
		D	2.26	0		33.33	1.54	66.67
		E*	1.76	0		0	0	0
		G	2.26	1.26		33.33	.51	40.00
		Combined	2.14	.88	.64	33.29	.77	50.00
1591	190	B	3.16	0		0	0	0
		C	3.07	3.77		48.88	5.70	80.77
		D	3.95	-1.06		46.67	1.10	36.36
		Combined	3.39	- .14	2.26	31.04	2.27	67.57

* First or second of five segments interpreted by analyst.

TABLE B.8 INTERPRETATION TEST RESULTS: ALFALFA/PASTURE/RANGE

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	% Commission (B)
145	172	B*	35.47	2.61		91.80	8.56	14.50
		C*	38.95	3.49		98.51	6.67	9.59
		E*	30.72	-.59		82.34	6.99	16.07
		Combined	35.05	1.84	2.54	91.52	7.41	13.05
185	186	A*	5.91	-1.34		68.18	.57	11.76
		C*	7.53	7.53		78.57	8.14	21.43
		D*	6.72	7.29		76.00	2.31	29.63
		Combined	6.72	6.45	6.10	74.66	1.54	22.22
241	195	A	32.56	0		85.83	6.85	14.17
		C	34.53	10.25		94.80	18.41	26.91
		F	29.74	- .25		75.00	10.22	24.35
		G*	32.31	3.76		92.06	9.34	17.53
		Combined	32.29	35.73	5.46	87.29	11.14	21.11
824	205	B	3.17	3.60		100.00	3.78	53.57
		D*	5.37	7.31		100.00	7.73	57.69
		F	2.93	.48		100.00	.50	14.29
		G	2.20	.48		88.89	.75	27.27
		Combined	3.40	3.00	4.09	98.21	3.16	47.62
854	204	C	4.90	.74		85.00	1.55	26.09
		E	4.66	2.69		100.00	2.8[illegible]	36.67
		F*	3.88	-2.21		26.67	.51	33.33
		G	4.66	3.43		89.47	1.54	18.18
		Combined	4.47	1.17	2.47	78.08	2.25	38.04

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	% Commission (B)
883	191	D	18.32	1.31		82.86	5.45	22.67
		E	17.02	-8.64		29.23	4.10	40.63
		F	17.54	-6.02		53.73	2.54	18.18
		G*	20.94	1.31		80.00	6.95	24.71
		Combined	18.46	-3.01	5.35	62.77	4.74	25.00
886	204	A	13.48	6.00		52.73	7.37	47.37
		B	14.22	7.84		96.55	9.71	37.78
		E	13.97	4.66		91.23	6.84	31.58
		Combined	13.89	4.17	5.27	80.59	7.97	38.00
1075	205	A*	55.12	.97		92.92	5.31	5.41
		B*	60.89	2.93		96.00	8.81	8.41
		F*	55.94	-8.3		79.6[illegible]	6.64	6.18
		Combined	57.31	-2.16	5.15	89.65	6.52	6.78
1572	199	A	76.38	2.05		98.68	12.77	3.85
		D	77.14	2.76		96.09	23.08	6.65
		E*	78.14	6.78		99.36	34.48	8.88
		G	77.39	6.28		99.35	30.00	8.11
		Combined	77.20	4.46	4.87	98.37	24.86	6.92
1591	190	B	61.22	17.63		99.14	47.62	23.33
		C	58.86	- .75		33.78	14.51	11.38
		D	58.85	16.05		95.08	46.05	25.29
		Combined	58.27	12.37	13.77	96.09	35.11	20.77

* First or second of five segments interpreted by analyst.

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TABLE B.9 INTERPRETATION TEST RESULTS: IDLE

Segment	#Pixels	Analyst	P(%)	AT Error	RMS	% Correct	% Commission (A)	% Commission (B)
145	172	B*	.58	1.16		0	1.75	100.00
		C*	.58	- .58		0	0	0
		E*	.58	1.16		0	1.17	100.00
		Combined	.58	.97	1.00	0	.97	100.00
185	186	A*	1.61	- .53		33.33	.53	50.00
		C*	1.61	-1.34		16.67	0	0
		D*	1.88	-1.07		28.57	.27	33.33
		Combined	1.70	- .98	1.10	26.32	.27	37.50
241	195	A	3.85	0		40.00	2.40	60.00
		C	5.38	-10.50		0	0	0
		F	3.59	0		57.14	1.60	42.86
		G*	3.85	-2.57		13.33	.80	60.00
		Combined	4.17	-1.99	5.40	24.62	1.20	52.94
854	204	C	.98	- .98		0	0	0
		E	.41	.81		0	1.23	100.00
		F*	.98	.98		50.00	1.49	75.00
		G	1.22	0		0	0	0
		Combined	.90	- .10	.80	13.64	.68	84.61
883	191	D	.26	- .26		0	0	0
		E	1.05	0		50.00	.53	50.00
		F	1.05	0		50.00	.53	50.00
		G*	1.05	-1.05		0	0	0
		Combined	.85	- .33	.54	30.77	.26	50.00

Segment	#Pixels	Analyst	P(%)	AT Error	RMS	% Correct	% Commission (A)	% Commission (B)
886	204	A	.49	1.47		0	1.97	100.00
		B	0	2.21		0	2.11	100.00
		E	.98	.98		50.00	1.49	75.00
		Combined	.49	1.55	1.63	33.33	1.89	92.00
1075	205	A*	2.20	.73		46.66	1.30	46.67
		B*	2.84	-1.70		31.39	.25	22.46
		F*	2.68	- .73		54.55	.50	25.00
		Combined	2.57	- .57	1.15	43.13	.92	44.61
1572	199	A	6.28	-1.51		68.00	.56	19.53
		D	6.03	- .75		75.00	.80	14.29
		E*	6.28	-2.00		68.00	0	0
		C	4.52	-3.01		33.33	0	0
		Combined	5.78	-1.82	1.99	63.04	.33	7.94
1591	190	B	8.66	-3.51		7.69	1.13	86.67
		C	8.68	-3.15		48.48	1.44	21.81
		D	6.84	-2.10		42.31	1.98	38.89
		Combined	7.44	-3.51	2.98	34.17	1.52	35.56

* First or second of five segments interpreted by analyst.

TABLE B.10 INTERPRETATION TEST RESULTS: NON-AGRICULTURE

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	% Commission (B)
145	172	B*	9.89	-5.53		38.24	.65	13.33
		C*	13.67	-2.91		74.47	.67	5.41
		E*	15.22	12.02		71.95	1.25	8.85
		Combined	12.92	9.04	7.82	64.24	.85	8.21
185	186	A*	11.56	1.07		100.00	1.23	8.65
		C*	8.37	.54		100.00	.60	5.71
		D*	13.44	0		98.00	.31	2.00
		Combined	11.29	1.05	.69	99.21	.71	5.30
241	195	A	6.32	0		100.00	0	0
		C	3.50	0		85.36	.53	14.64
		F	4.62	-1.54		66.67	0	0
		G*	6.84	0		88.75	.83	11.25
		Combined	5.32	- .38	.77	86.75	.54	6.49
824	205	B	9.02	- .73		91.89	0	0
		D*	15.37	1.22		100.00	1.44	7.35
		F	4.88	- .49		90.00	0	0
		G	10.73	2.20		97.73	.64	18.87
		Combined	10.00	.55	1.33	96.34	1.02	8.67
854	204	C	7.27	.24		100.00	.23	3.26
		E	5.15	.24		85.71	1.03	18.18
		F*	6.78	.49		89.15	1.31	16.86
		G	5.88	0		100.00	0	0
		Combined	6.27	.25	.29	94.14	.65	9.40

Segment	#Pixels	Analyst	P(%)	AI Error	RMS	% Correct	% Commission (A)	% Commission (B)
883	191	D	18.06	0		100.00	0	0
		E	17.80	3.67		100.00	4.46	17.07
		F	13.26	1.57		100.00	1.81	10.59
		G*	12.83	1.05		85.71	.90	6.67
		Combined	15.49	1.05	2.06	96.76	1.78	9.10
886	204	A	18.83	-1.51		90.75	2.64	2.83
		B	9.80	-3.92		55.00	.54	8.33
		E	15.28	-1.72		85.56	.58	3.61
		Combined	14.54	-2.29	2.62	80.90	.57	4.00
1075	205	A*	11.95	1.22		100.00	1.39	9.26
		B*	6.83	-1.46		67.86	.79	13.64
		F*	9.76	0		90.00	1.08	10.00
		Combined	9.51	.08	1.10	88.89	1.08	10.34
1572	199	A	3.27	- .25		61.54	1.04	33.33
		D	2.01	-2.01		0	0	0
		E*	2.51	-2.26		10.00	0	0
		G	1.75	-1.00		14.29	.51	66.67
		Combined	2.39	1.00	1.60	26.32	.39	37.50
1591	190	B	10.00	-7.89		15.79	.58	25.00
		C	12.54	7.54		58.75	.20	7.30
		D	10.96	-10.00		6.39	.30	27.32
		Combined	11.17	3.54	8.55	28.79	.36	9.07

* First or second of five segments interpreted by analyst.

Appendix C

Analysis of variance tables and computations for Scheffé's multiple comparison test for the guidelines interpretation test results. See Section 2.3.3 in the body of this report for the definition of the variables within the following tables.

Table C.1

ANOVA - % Correct - Corn

		Analyst							
		A	**B**	**C**	**D**	**E**	**F**	**G**	**Total**
Segment	**241**	97.91		88.91			94.17		280.99
	824		88.27				96.15	98.29	282.71
	854			100.00		99.04		96.50	295.54
	883				88.33	97.69	88.67		274.69
	886	94.43	90.36			94.35			279.14
	1572	81.82			85.11		92.45		259.38
	1591		19.30	45.16	35.29				99.75
	Total	274.16	197.93	234.07	208.73	291.08	278.99	287.24	1772.20

$\Sigma Y_{i\cdot}^2 = 476825.9984$ $\Sigma Y_{\cdot j}^2 = 457766.7724$ $\Sigma\Sigma Y_{ij}^2 = 159512.1538$

Source	Sum of Squares	d.f.	Mean Square	F	Significance
Segments	9385.1976				
Analysts (adjusted)	309.0342	6	51.5057	1.578	ns
Analysts	3032.1222				
Segments (adjusted)	6662.1096	6	1110.3516	34.018	.001
Residual	261.1201	8	32.6400		
Total	9955.3519	20			

Table C.2

ANOVA - % Correct - Summer Crops

		Analyst							
		A	B	C	D	E	F	G	Total
Segment	241	80.59		82.00			72.39		234.98
	824		89.27				91.42	96.26	276.95
	854			95.79		94.70		92.07	282.56
	883				85.54	93.47	90.78		269.79
	886	93.00	90.10			94.92			278.02
	1572	76.60			80.00			87.50	244.10
	1591		21.13	46.25	35.30				102.68
	Total	250.19	200.50	224.04	200.84	283.09	254.59	275.83	1689.08

$\Sigma Y_{i\cdot}^2 = 431966.8134$ $\Sigma Y_{\cdot j}^2 = 414364.1184$ $\Sigma\Sigma Y_{ij}^2 = 144499.4928$

Source	Sum of Squares	d.f.	Mean Square	F	Significance
Segments	8132.2118				
Analysts (adjusted)	349.3401	6	58.2234	2.889	ns
Analysts	2264.6468				
Segments (adjusted)	6216.9051	6	1036.1509	51.417	.001
Residual	161.2149	8	20.1519		
Total	8642.7668	20			

Table C.3

ANOVA - Commission A - Corn

		Analyst							
		A	**B**	**C**	**D**	**E**	**F**	**G**	**Total**
Segment	**241**	7.47		4.42			18.12		30.01
	824		6.93				10.08	2.12	19.13
	854			7.41		1.00		9.34	17.75
	883				8.02	7.94	5.03		20.99
	886	2.43	3.32			.84			6.59
	1572	1.41			1.42			.58	3.41
	1591		1.24	0	2.78				4.02
	Total	11.31	11.49	11.83	12.22	9.78	33.23	12.04	101.90

$\Sigma Y_{i\cdot}^2 = 2093.4162$ $\Sigma Y_{\cdot j}^2 = 1894.0564$ $\Sigma\Sigma Y_{ij}^2 = 884.8458$

Source	**Sum of Squares**	**d.f.**	**Mean Square**	**F**	**Significance**
Segments	203.3478				
Analysts (adjusted)	73.3078	**6**	12.2180	.859	ns
Analysts	136.8945				
Segments (adjusted)	139.7613	**6**	23.3935	1.646	ns
Residual	113.7326	**8**	14.2166		
Total	390.3882	**20**			

Table C.4

ANOVA - Commission B - Corn

		Analyst							
		A	B	C	D	E	F	G	Total
Segment	241	19.02		13.18			34.90		67.10
	824		9.20				11.61	2.82	23.63
	854			7.37		3.28		8.96	19.61
	883				16.54	13.60	10.60		40.74
	886	3.78	3.78			1.22			8.78
	1572	12.20			11.11			3.92	27.23
	1591		26.67	0	31.03				57.70
	Total	35.00	39.65	20.55	58.68	18.10	57.11	15.70	244.79

$\Sigma Y_{i.}^2 = 11252.9379$ $\Sigma Y_{.j}^2 = 10498.4195$ $\Sigma\Sigma Y_{ij}^2 = 4688.9693$

Source	Sum of Squares	d.f.	Mean Square	F	Significance
Segments	897.5439				
Analysts (adjusted)	598.8846	6	99.8141	2.355	ns
Analysts	646.0377				
Segments (adjusted)	850.3908	6	141.7318	3.344	ns
Residual	339.1054	8	42.3882		
Total	1835.5339	20			

Table C.5

ANOVA - Commission B - Summer Crops

		Analyst							
		A	B	C	D	E	F	G	Total
Segment	241	14.79		17.03			17.88		49.70
	824		8.14				7.55	1.74	17.43
	854			3.62		2.02		5.52	11.16
	883				7.56	1.20	5.85		14.61
	886	1.21	5.96			3.65			10.82
	1572	15.55		15.38				0	30.93
	1591		70.77	49.00	52.12				171.89
	Total	31.55	84.87	69.65	75.06	6.87	31.28	7.26	306.54

$\Sigma Y^2_{i.} = 33731.8020$ $\Sigma Y^2_{.j} = 19761.7884$ $\Sigma\Sigma Y^2_{ij} = 11749.7628$

Source	Sum of Squares	d.f.	Mean Square	F	Significance
Segments	6769.3258				
Analysts (adjusted)	258.5620	6	43.0937	1.394	ns
Analysts	2112.6546				
Segments (adjusted)	4915.2332	6	819.2055	26.504	.001
Residual	247.2668	8	30.9084		
Total	7275.1546	20			

Table C.6

ANOVA - AI Proportion Estimate Error - Corn

		Analyst							
		A	**B**	**C**	**D**	**E**	**F**	**G**	**Total**
Segment	**241**	5.13		.60			11.80		17.53
	824		-1.22				3.90	.49	3.17
	854			3.84		1.23		2.94	8.01
	883				1.84	4.45	-.26		6.03
	886	-.73	-2.94			-1.88			-5.55
	1572	-.76			-.50			-.51	-1.77
	1591		-11.05	-8.95	-7.28				-27.28
	Total	3.64	-15.21	-4.51	-5.94	3.80	15.44	2.92	.14

$\Sigma Y_{i.}^2 = 1196.0046$ $\Sigma Y_{.j}^2 = 561.5774$ $\Sigma\Sigma Y_{ij}^2 = 500.0152$

Source	**Sum of Squares**	**d.f.**	**Mean Square**	**F**	**Significance**
Segments	398.6673				
Analysts (adjusted)	38.7737	**6**	6.4623	.826	ns
Analysts	187.1916				
Segments (adjusted)	250.2494	**6**	41.7082	5.332	.025
Residual	62.5733	**8**	7.8217		
Total	500.0143	**20**			

Table C.7 Scheffé's Multiple Comparisons Procedure

Adjusted Estimates of Segment Effects

	886	241	1572	1591	824	854	883
1. % Correct - Corn	10.62	7.96	1.14	-48.78	12.00	10.60	6.47
2. % Correct - Summer Crops	14.33	-3.41	.78	-45.33	14.28	9.25	10.12
3. Commission B - Summer Crops	-12.98	2.37	-3.01	40.87	-10.16	-7.19	-9.91
4. AI Proportion Estimate Error - Corn	-1.27	5.43	-.85	-8.03	.91	3.12	.68

Test of H_o: $C = b_1 + b_2 + b_3 - 6b_4 + b_5 + b_6 + b_7 = 0$ (i.e., segment 1591 is significantly different from the mean of all other segments)

1. % Correct - Corn: $\hat{C} = 341.47$, $K = 212.92$ (for $\alpha = .001$), reject H_o.

2. % Correct - Summer Crops: $\hat{C} = 317.33$, $K = 167.30$ (for $\alpha = .001$), reject H_o.

3. Commission B - Summer Crops: $\hat{C} = -286.10$, $K = 207.19$ (for $\alpha = .001$), reject H_o.

4. AI Proportion Estimate Error - Corn: $\hat{C} = 56.20$, $K = 54.99$ (for $\alpha = .05$), reject H_o.

Table C.8 t-Tests for Learning Effect

Data Used:

Segment	First Analyst	Last Analyst
824	D	B
854	F	C
883	G	F
1572	E	A

Results:

Variable of Interest	t-Value
% Correct - Corn	.39
Commission A - Corn	-.58
Commission B - Corn	-.67
AI Proportion Error - Corn	-.17
* % Correct - Soybeans	1.98
* Commission A - Soybeans	.20
* Commission B - Soybeans	-.06
* AI Proportion Error - Soybeans	1.62
% Correct - Summer Crops	.74
Commission B - Summer Crops	.62

All t-values are non-significant at the .05 level

* Segment 1572 excluded due to absence of soybeans in sampled pixels.